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Artificial neural network model for precipitation forecast over Western Himalaya using satellite images

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सार – भारत मौसम विज्ञान विभाग (IMD) द्वारा उपलब्ध वास्तविक समय में कल्पना उपग्रह छवियों में इन्फ्रा-रेड (IR), जल वाष्प (WV), और दृश्यमान (VIS) बैंड में क्लाउड के बारे में प्रासंगिक इनपुट होते हैं। वर्तमान अध्ययन में आईआर और डब्ल्यूवी छवियों के निकाले गए ग्रे स्केल मानों का उपयोग करके पश्चिमी हिमालय के छह स्टेशनों पर वर्षा की भविष्यवाणी करने का प्रयास किया गया है। किसी स्थान पर निकाले गए पिक्सेल मानों को उस स्थान पर संबंधित वर्षा के लिए प्रशिक्षित किया जाता है। 0300 यूटीसी पर वर्षा की स्थिति को 24 घंटे के लीड समय के साथ वर्षा पूर्वानुमान के लिए मॉडल को प्रशिक्षित करने के लिए माना जाता है। आईआर (10.5 - 12.5 माइक्रोन) और डब्ल्यूवी (5.7 - 7.1 माइक्रोन) बैंड में प्राप्त उपग्रह छवियों का उपयोग गुणात्मक और मात्रात्मक वर्षा पूर्वानुमान के लिए कृत्रिम तंत्रिका नेटवर्क (एएनएन) मॉडल विकसित करने के लिए किया गया है। मॉडल के परिणामों को जमीनी टिप्पणियों के साथ मान्य किया जाता है और परिचालन उद्देश्य के लिए मॉडल की क्षमता की जांच करने के लिए कौशल स्कोर की गणना की जाती है। छह स्टेशनों पर पता लगाने की संभावना पीर-पंजाल रेंज में गुलमर्ग के लिए 0.78 से लेकर ग्रेटर हिमालयन रेंज में द्रास के लिए 0.95 तक है। गुणात्मक पूर्वानुमान के लिए समग्र प्रदर्शन 61% से 84% के बीच है। अध्ययन के तहत विभिन्न स्थानों के लिए मूल माध्य वर्ग त्रुटि 5.81 से 8.7 के बीच है।

ABSTRACT. Kalpana satellite images in real time available by India meteorological department (IMD), contain relevant inputs about the cloud in infra-red (IR), water vapor (WV), and visible (VIS) bands. In the present study an attempt has been made to forecast precipitation at six stations in western Himalaya by using extracted grey scale values of IR and WV images. The extracted pixel values at a location are trained for the corresponding precipitation at that location. The precipitation state at 0300 UTC is considered to train the model for precipitation forecast with 24 hour lead time. The satellite images acquired in IR (10.5 - 12.5 µm) and WV (5.7 - 7.1 µm) bands have been used for developing Artificial Neural Network (ANN) model for qualitative as well as quantitative precipitation forecast. The model results are validated with ground observations and skill scores are computed to check the potential of the model for operational purpose. The probability of detection at the six stations varies from 0.78 for Gulmarg in Pir-Panjal range to 0.95 for Dras in Greater Himalayan range. Overall performance for qualitative forecast is in the range from 61% to 84%. Root mean square error for different locations under study is in the range 5.81 to 8.7.

Key words – ANN, Forecast, Precipitation, Satellite images.

1. Introduction

Accurate and timely prediction of weather has a large impact on our day to day activities, water resources, agriculture and the economy of the country. There are several method used for forecasting the weather in space and time. In early periods persistent methods were used for forecasting weather, which uses the current situation of meteorological parameters to forecast weather locally. Subsequently stochastic methods were developed based on the tele-connections of the meteorological parameters for forecasting weather. With these models, different methods such as regression analysis, artificial neural network, hidden markov chain, Bays' statistics etc. were used as the statistical tools. To develop these types of statistical models, a large historical data are required. In the absence of large observed data base, NWP models are simulated to generate these data base by using global boundary conditions. However due to coarse horizontal resolution of the NWP models and the inherent error present in the output, these data become less useful as long as operational weather forecast over an area is concerned. With the development of remote sensing techniques with time, satellite products are now being used to improve the accuracy of forecast in NWP models by data assimilation in real time. The satellite data are also very useful in bridging the gaps of the data sparse region.

Satellites provide the real time data of the atmosphere. The first geostationary meteorological satellite observations started in 1966 and was followed by other meteorological satellites (Brugge and Stuttard, 2003). Geostationary satellites are positioned about 36000 km over the Equator with an orbital period of 24 hours. INSAT cloud imagery data is used as a reference for the evaluation of cloudiness prediction performance of WRF model (Shah *et al.*, 2010). Many types of satellite observations are directly used in NWP models. At present satellite data is the most important source for the atmospheric data (Collard, 2011). Yaiprasert *et al*. (2007) used pixel values of GOES-9 satellite image for forecasting possible rainfall area in Thailand. Lucas *et al*. (2007) developed a rule based classification of satellite imagery for land cover mapping. Dalu (1986) discussed the satellite remote sensing of water vapor in the atmosphere.

Kalpana-1 satellite provides images in Visible (VIS), Infra-red (IR) and Water Vapor (WV) bands at every half an hour interval. These images provide the information about the cloud movement and water content present in the atmosphere. Kalpana-1 located at Longitude 74° E is a geostationary satellite and is being used to monitor the weather of the Indian region. For meteorological observation, Kalpana -1 Satellite carries a three channel Very High Resolution Radiometer (VHRR) with 2 km resolution in the visible band and 8 km resolution in thermal infrared and water vapor bands.

VIS (0.55-0.45 µm) imagery is derived from solar radiation scattered or reflected towards the satellite from the earth - atmosphere system. The intensity of the image depends on the albedo or reflectivity of the underlying surface or cloud. In general clouds are seen as white object against the darker background of the earth's surface.

IR (10-12 µm) imageries are derived from terrestrial radiation emitted in the 10-12 µm regions and this provides information on the temperature of the underlying surface or cloud. The IR radiation with the lowest intensity is emitted by the highest and coldest clouds and these appear white.

WV (6-7 µm) imagery is derived from the radiation emitted by water vapour at wavelengths which are not in an atmospheric window. Emission from water vapour at

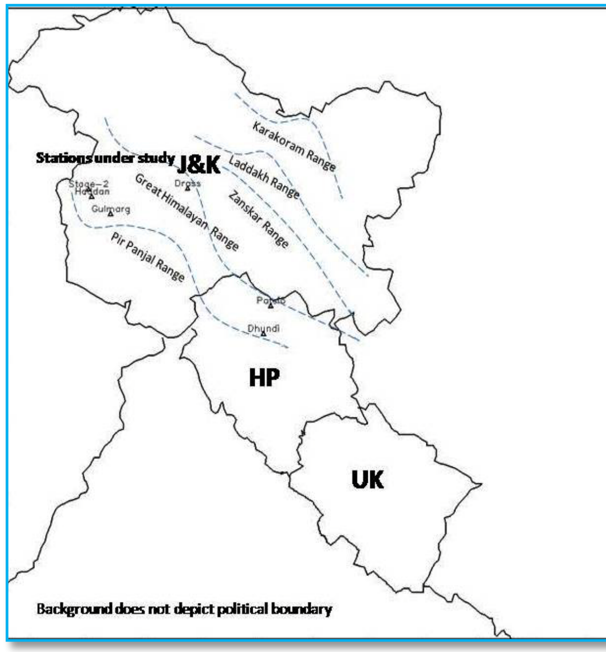


Fig. 1. Observatory network in western Himalaya showing the stations under study

low levels in the atmosphere therefore not normally escapes to space. If the upper troposphere is moist, the radiation reaching the satellite mostly originates from this region (cloud) and is displayed in white shades (Bader *et al*., 1995).

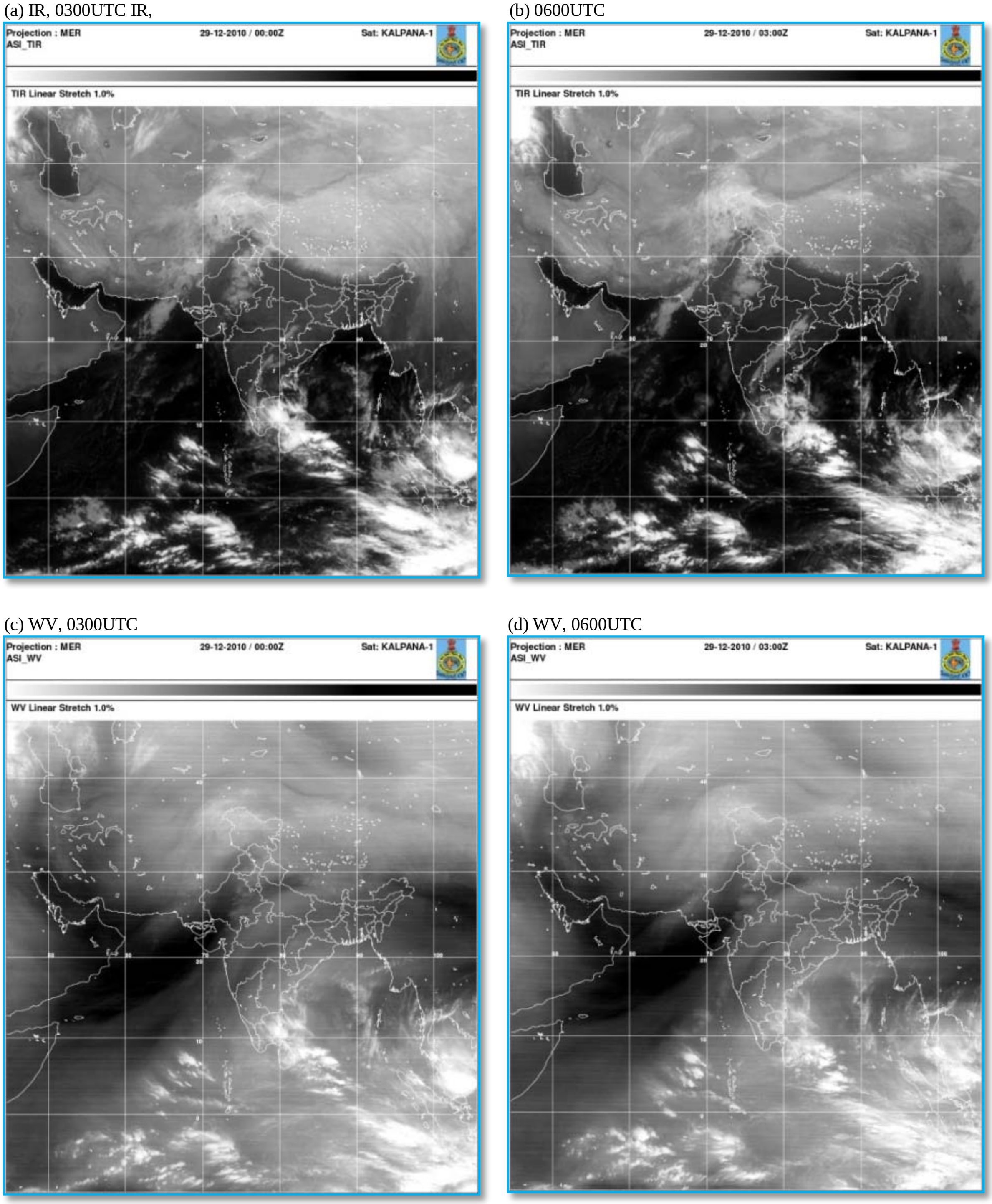
In this paper, pixel values (grey scale values 0 to 255) of Infra-Red (IR) and Water Vapour (WV) images from geostationary Kalpana satellite (from India Meteorological Department) havebeen extracted. An artificial neural network (ANN) model has been developed using the pixel values and the observed precipitation with 24 hour lead time. Data used and methodology have been discussed in section 2. Results and conclusions have been given in section 3 and section 4 respectively.

2. Data and methodology

Six locations namely Stage II, Haddantaj, Gulmarg, Dhundi, Drass and Patsio over various ranges of western Himalaya have been considered for the present study (Fig. 1). The data set consists of IR and WV images at 0300 UTC and 0600 UTC from November 2010 to March 2011and November 2012 to April 2013. This data set is divided into two. Data from November 2010 to March 2011are taken as training set and data from Nov 2012 to April 2013 are taken as independent data set for the validation of model results. Figs. 2(a-d) shows the IR and WV images at0300 UTC and 0600 UTC.

(a) IR, 0300UTC IR, (b) 0600UTC

(c) WV, 0300UTC (d) WV, 0600UTC



Figs. 2(a-d). IR images of Kalpana Satellite at (a) 0300 UTC, (b) 0600 UTC, (c) WV images of Kalpana Satellite at 0300 UTC and (d) WV images of Kalpana Satellite at 0600 UTC

MATLAB software is used to develop algorithm for extracting pixel values (grey scale values) of IR and WV images at a grid of 8 × 8 pixels corresponding to each location. The mean value has been calculated which represents the final value of the pixel of that station. Thus for one observatory there are four values per day, *i.e.*, two from WV and two from IR images. Corresponding to these pixel values, precipitation (mm) amount at each

TABLE 1

Pixel values and corresponding precipitation at different stations on 29 December, 2010

Station	Altitude (m)	WV (0300 UTC)	WV (0600 UTC)	IR (0300 UTC)	IR (0600 UTC)	PPT (0300 UTC 24 hr lead time)
Gulmarg	2800	184	185	182	202	44.20
Haddan Taj	3080	205	201	219	213	33.40
Stage II	2650	197	192	213	207	18.00
Dras	3250	180	176	181	163	10.50

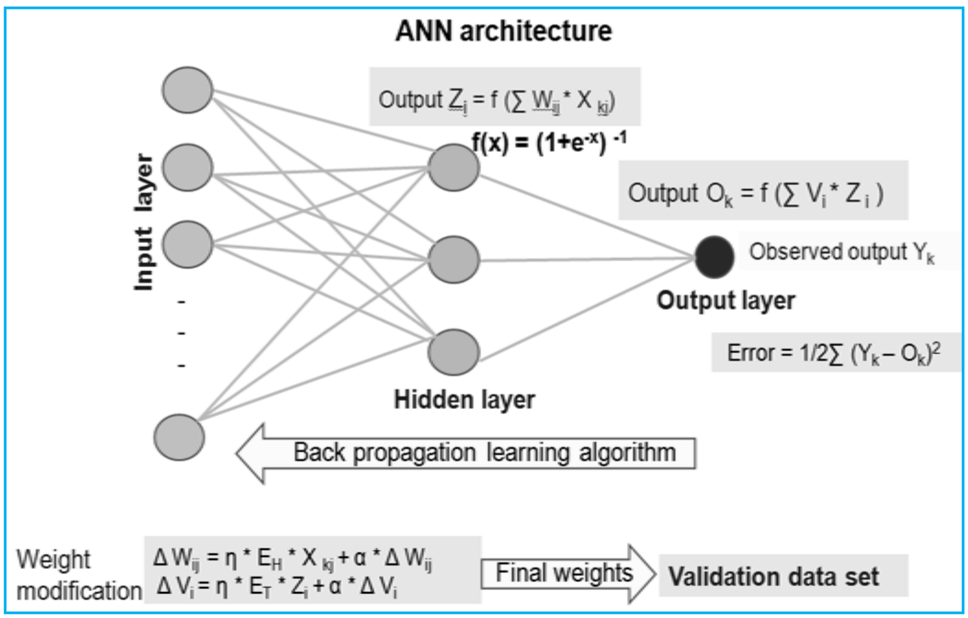


Fig. 3. Schematic diagram of multi layered ANN

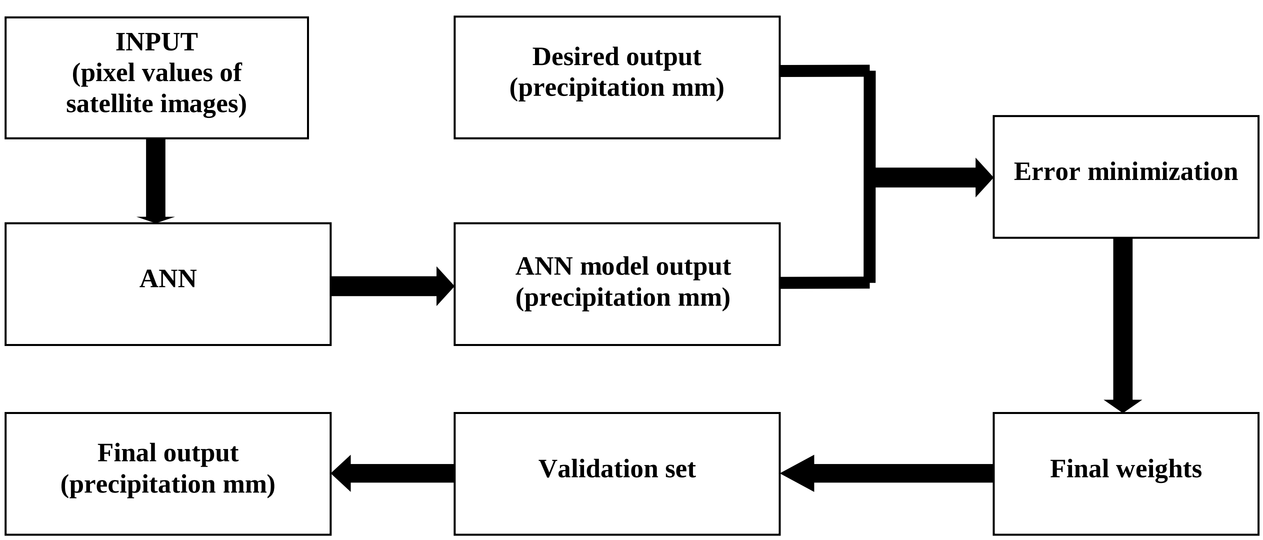
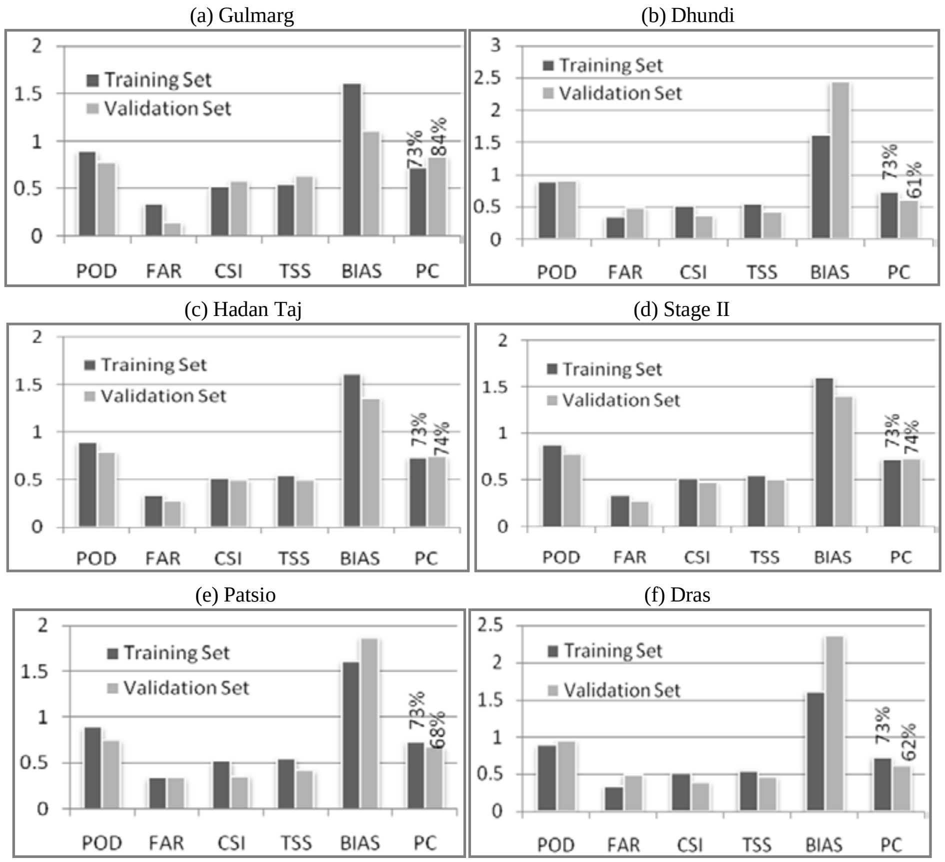


Fig. 4. Flow chart of methodology



Figs. 5(a-f). Skill scores for qualitative precipitation forecast

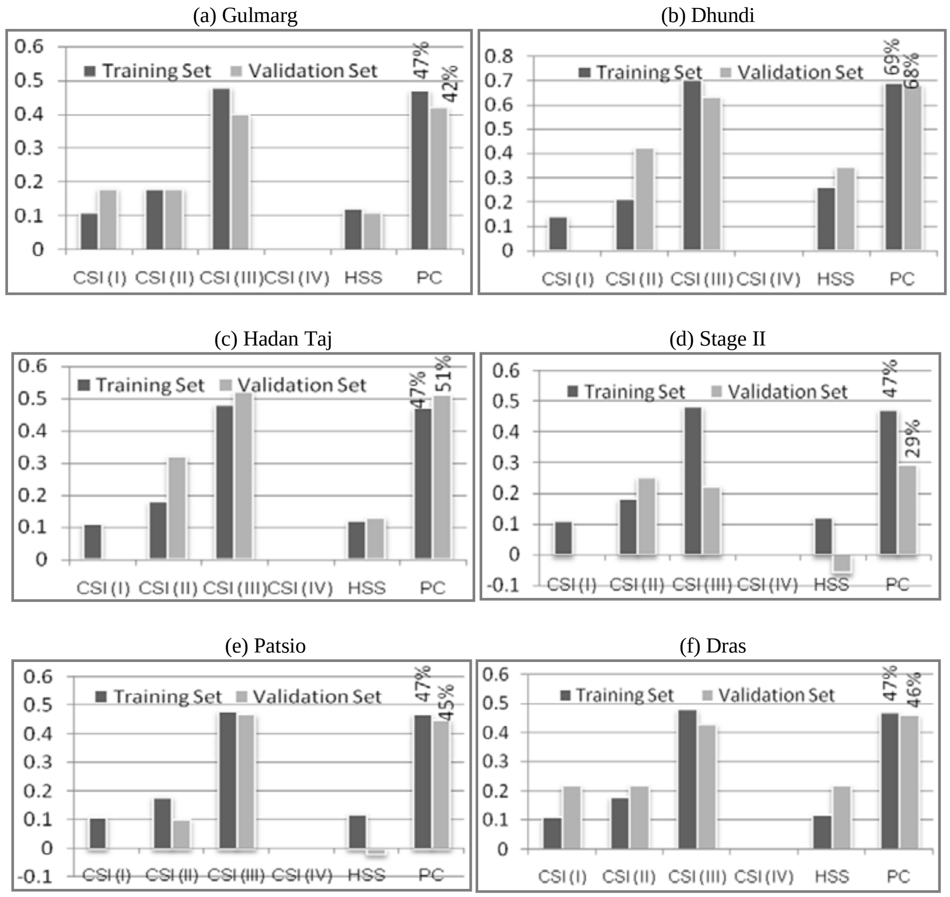
location with 24 hour lead time has been considered. Extracted pixel values and associated precipitation on 29th December, 2010 for different stations along with their altitude have been given in Table 1.

Relationship between the extracted pixel values and associated precipitation is modeled using a three-layer Artificial Neural Network (ANN) (Joshi *et al*., 2012). Pixel values and precipitation are taken as input and output to ANN respectively. Back propagation learning algorithm is used for training. There are total 1012 data points out of which 785 data points are taken for training purpose and 227 points are taken as independent data set for the validation of developed model. Single hidden layer with seven hidden nodes is used in the present study. Data is normalized between 0.1 and 0.9 and sigmoid transfer function $f(x) = (1+e^{-x})^{-1}$ is applied for the calculation of the outputs at both the hidden and output layers. Fig. 3 shows the schematic diagram of multi layered ANNand Fig. 4 depicts the flow diagram of complete methodology. Thus the visual interpretation of the images is quantitatively converted in an ANN model using the extracted pixel values of the images.

2.1. *Back propagation learning algorithm*

In Back propagation algorithm the error is back propagated and respectively the weights are adjusted so as to reduce the error. The iteration continues until target value with minimum error is reached (Gill *et al*., 2010). At the beginning of the training process, random weights are assigned to the network. The data set is splitted into training set and test set. During the training process, the input and output data from the training data subset are fed into the network. The error between training output and actual output values is then calculated and propagated successively from the output layer to the first layer via the backpropagation algorithm. Weights of the connections between neurons are adjusted and it is repeated to minimize the error. More the input data set used for training accurate will be the result, as it will have more data available for training (Naik *et al*., 2012).

In the present study three-layer ANN is developed with single hidden layer and seven hidden nodes. The activation function is a sigmoid transfer function $(1+e^{-x})^{-1}$, for both input-hidden layer and hidden output layer.



Figs. 6(a-f). Skill scores for quantitative precipitation forecast

Weights are adjusted in such a way that the error, the difference between the network output and desired output is reduced. This error is propagated backward to the hidden layer and weights are modified. The weights are adjusted so as to minimize the error.

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. The model is developed for qualitative and quantitative precipitation forecast over six stations in western Himalaya.

3. Results and discussion

In the present study an ANN model using satellite images is developed for precipitation forecast over western Himalaya.

3.1. *Qualitative forecast*

For qualitative forecast, the occurrence and nonoccurrence of precipitation events is considered. Different skill scores are calculated for the verification of forecast using 2 × 2 contingency table for training as well as validation set (Wilks, 1995). For Gulmarg Probability of Detection (POD), *i.e.*, the right forecast is 0.89 for training set and 0.78 for the validation set. The ideal score for POD is 1. Thus, the POD of the model is fairly good. The False Alarm (FAR) is 0.34 and 0.14 for the training and validation set respectively which is relatively low indicating the good performance of the model for Gulmarg.

Critical Success Index (CSI) and true skill scores (TSS) of the model are 0.52 and 0.55 for the training set and 0.58 and 0.64 for the validation set which also falls in acceptable range. The model BIAS for training set it is 1.61 and for validation set is 1.1. The overall accuracy of the model is calculated in terms of percent correct which is84% with the independent data set (Fig. 5).

Similarly, for Haddan Taj, POD is 0.79 for validation set, FAR is 0.28, CSI and TSS are 0.5 and 0.5 and model BIAS is 1.36. The accuracy of themodel is 74%.

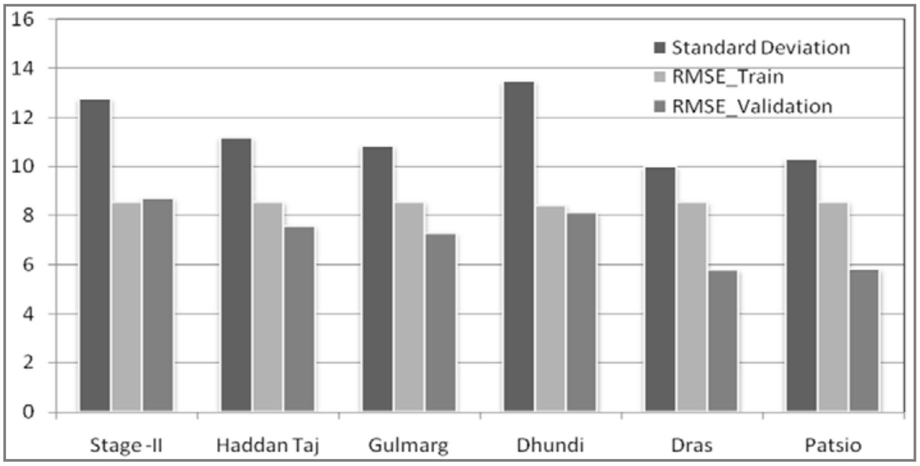


Fig. 7. RMSE for quantitative precipitation forecast

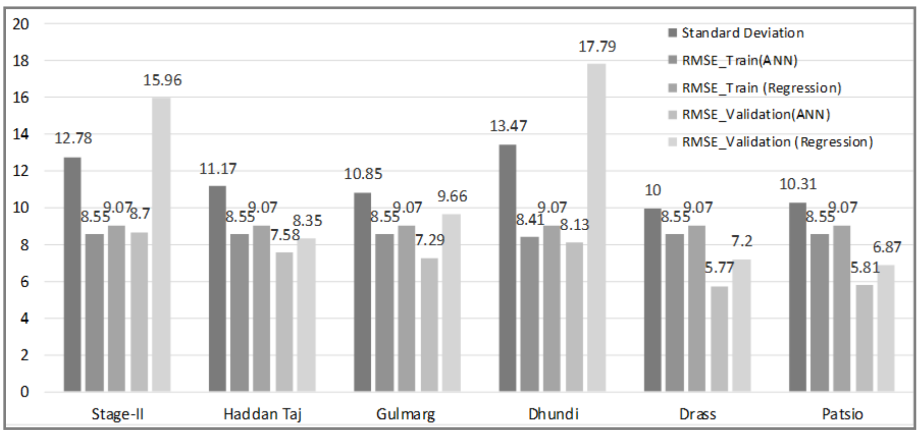


Fig. 8. Comparison of ANN model and multiple Regression model

For Patsio corresponding to validation set, POD is 0.75; FAR of the model is 0.34. CSI and TSS of the model are 0.36 and 0.42 for the validation set. The model BIAS is 1.87 for Patsio which is slightly high. Higher BIAS shows that model is over predicting the precipitation. The overall accuracy of the model is 68% for Patsio. The skill scores for all the stations are given in Fig. 5.

3.2. *Quantitative forecast*

For quantitative analysis, the precipitation has been divided into following four categories.

Category I : <2.4 mm

Category II : 2.5 to 7.5 mm

Category III : 7.6 to 35.5 mm

Category IV : > 35.5 mm

To verify the skill of the model critical success index in different categories is calculated using 4 × 4 contingency table. Corresponding to Gulmarg, CSI for training set is 0.11, 0.18, 0.48 and 0.0 in the category I, II, III and IV respectively while for validation set CSI is 0.18, 0.18, 0.4 and 0.0 in different categories. In category III the value of CSI is highest for both the cases. It indicates that the most of the time the precipitation falls in this category for the period under study. In category IV CSI is 0. Thus model could not capture this category for Gulmarg. The Heidke skill score (HSS) is 0.12 and 0.11 for training and validation set. Accuracy of categorical quantitative precipitation is 47% and 42% for the training and validation set respectively (Fig. 6). Again to check the performance of the model, root mean square error (RMSE) is calculated (Fig. 7). Corresponding to Gulmarg RMSE is 8.55 and 7.29 for the training set and validation set respectively. The standard deviation (SD) of the data is 12.78. The RMSE is less than the standard deviation indicating fairly good performance of the model.

Corresponding to Haddan Taj, CSI for validation set is 0, 0.32, 0.52 and 0 in the category I, II, III and IV respectively. In this case CSI is 0 for category I and IV and for category III it is highest. HSS is 0.13 and categorical quantitative precipitation accuracy is 51% for HaddanTaj. RMSE is 7.58 and less than the SD (11.17).

For Patsio location, CSI corresponding to validation set in different categories is 0, 0.1, 0.47 and 0 and HSS is -0.02. Forecast accuracy in different category is 45%. RMSE for Patsio is 5.81 which is quite less than the standard deviation 10.31, showing the good performance of the model. Fig. 6 and Fig. 7 represent the result for all stations.

3.3. *Multiple regression analysis*

Multiple regression analysis with same input and output parameters for training and test set was carried out for all the six locations to test the skill of the proposed artificial neural network. For Haddan Taj station with respect to the training set RMSE for multiple regression is 9.07 and standard deviation is 11.17 and RMSE for validation set is 8.35. The RMSE being lower than the standard deviation, indicates the good performance of the model. This regression model is compared with ANN model. For ANN model RMSE for training set is 8.55 and for validation set it is 7.58, with same input, output parameters with respect to the same station. It is clear that the RMSE for training as well as validation set is lower in comparison to the RMSE with multiple regression model for the same station. Similar regression analysis has been carried out for all stations. The performance of both the models have been represented in Fig. 8. Results for all stations show that ANN model has better skill to predict the event, *i.e*., precipitation in present case, at any specific location due to its capability to capture the non-linearity associated with the system.

4. Conclusions

An ANN based model has been developed for precipitation forecast using Kalpana satellite images. The model extracts the pixel values corresponding to IR and WV images from the satellite to generate precipitation forecast over western Himalaya. Thus, the model is capable of interpreting satellite images in generalized manner without biasing. Results show good correspondence between pixel values and observed precipitation. Multiple regression model with same input and output parameters for training and validation data set was also developed for all the six locations and results were compared with the ANN model. Results show that ANN model has better skill to predict the precipitation at any specific location. Hence the ANN model can be used as a good supporting tool for operational weather forecast. The computational time is comparatively less. Limitation of the model is that the data is 8-bit and the maximum value of a pixel is 255. Therefore, mapping high precipitation value is difficult. In future surface meteorological parameters can be integrated with pixel values in input matrix for the enhancement of model performance.

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Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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