# Neural Method for Site-Specific Yield Prediction

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**Abstract** In the recent years, a variety of mathematical models relating to crop yield have been proposed. A study on Neural Method for Site –Specific Yield Prediction was undertaken for Jabalpur district using Artificial Neural Networks (ANN). The input dataset for crop yield modeling includes weekly rainfall, maximum and minimum temperature and relative humidity (morning, evening) from 1969 to 2010. ANN models were developed in Neural Network Module of MATLAB (7.6 versions, 2008). Model performance has been evaluated in terms of MSE, RMSE and MAE. The basic ANN architecture was optimized in terms of training algorithm, number of neurons in the hidden layer, input variables for training of the model. Twelve algorithms for training the neural network have been evaluated. Performance of the model was evaluated with number of neurons varied from 1 to 25 in the hidden layer. A good correlation was observed between predicted and observed yield (r = 0.898 and 0.648).

**Keywords** Artificial neural network · Crop yield · Site specific

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## 1 Introduction

Wheat (Triticum spp.) is a major crop of rabi season in India. It is cultivated in 28.52 Mha areas with the total production of about 80.71 million tons. The area, production and productivity of wheat in the states of Madhya Pradesh are 1.815 (Mha), 7.2796 MT, and 18.35 q/ha respectively [1]. The yield of this crop is very sensitive to temperature variation when soil moisture is less during the critical stages, which affect the productivity of wheat.

Yield patterns in fields may change annually, due to spatial variations in soil properties and weather. Climatic factors like temperature, solar radiation and rainfall affect crop yield. Changes in climatic variables like rise in temperature and decline in rainfall have been reported by Intergovernmental Panel on Climate Change [2]. Pre and post–anthesis high temperature and heat had massive impacts on wheat growth, whereas stress reduced its photosynthetic efficiency [3]. You et al. [4] observed a significant reduction in yield caused by a rise in temperature of 1.8 °C caused 3–10 % reduction in wheat yield. A few days of temperature above a threshold value, if coincident with anthesis, can significantly reduce yield by affecting subsequent reproductive processes [5].

A variety of nonlinear techniques for investigating yield response have also been examined, including boundary line analysis [6], state-space analysis Bayesian networks, and regression trees [7]. However, many nonlinear methods can be difficult to implement, and comparison of the results from these vastly different methods is problematic. Clearly, nonlinear methods that are relatively easy to implement and can be readily compared to one another would be highly desirable. A relatively new branch of nonlinear techniques, artificial neural networks (ANN or NN), has been applied not only to artificial intelligence [8] and classification applications [9] but also as general, non-parametric 'regression' tools.

Present study has been carried out to Estimate the yield of wheat crop in Jabalpur district based on climatic factors i.e. temperature, rainfall and relative humidity. The objective of the study is to develop an Artificial Neural Network model for wheat productivity for the Jabalpur district.

## 2 Study Area

Present study was carried out at Jabalpur district in Madhya Pradesh, India. It is located at latitude from 23009′36″N to 23037′N and longitude from 79057′E to 79095′E at the average MSL of 408 m within the Agro-Climatic zone of Kymore Plateau and Satpura hills. Jabalpur district has a humid subtropical climate, typical of North-Central India.

### 2.1 Collection of Data

Crop yield: Yield data of wheat and paddy crop of Jabalpur district was collected from the Department of Agricultural Economics and Farm Management, JNKVV, Jabalpur for the year 1969–2010. Yield data from 1969 to 1998 includes the yield of Katni district at present. The productivity of these crops has been computed from yield and area under the specific crop of the district.

Rainfall, temperature and humidity: The weekly data of rainfall, maximum and minimum temperature and relative humidity (morning, evening) of Jabalpur were collected from The Department of Physics and Agro-meteorology, College of Agricultural Engineering, JNKVV Jabalpur for the years 1969–2010.

### 2.2 Randomization of Data

Out of 41 years of data considered for the analysis, initially 25 years of data have been used for model development and rest for validation of the model. Due to separation of Katni district, from the Jabalpur in the year 1999, large variations in the productivity have been observed. In order to reduce the temporal effect on productivity, the total 41 years data have been randomized for the purpose of development and validation of the model.

### 2.3 Predictor Variables for Wheat

There are large variations in the duration of wheat crop in the district. To generalize the model, it is assumed that the wheat crop has an average crop period of twenty-two weeks that is from 44th Standard Metrological Week (SMW) to 13th SMW. The total number of predictor variable for this period becomes 110, hence to reduce the number of predictor variables model was developed with Principle Component Analysis (PCA). The predictor variables selected by PCA wheat crop and the model criteria set for (set of suitable input parameters based on correlation analysis between wheat yield and the selected input parameter [10]) is shown in Table 1.

## 3 Materials and Methods

The functional diagram of an artificial neuron is shown in Fig. 1. There are weighted input connections to the artificial neurons. These input signals get added up, and are fed into the activation function. The reaction signals of the neuron

**Table 1** ANN Models with varying input variable Model Predictors Criteria (PCA)

| Model | Predictors | Criteria (PCA) |
|---|---|---|
| WM-20 | T47 M47 M48 M51 M13 R47 R48 R50 T49 M6 R44 R46 R8 RHM2 RHM5 RHM6 RHE44 RHE45 RHE46 RHE11 | If r value is greater than 0.2 |
| WM-11 | T47 M47 M48 M13 R48 T49 R44 R46 RHM6 RHE44 RHE45 | If r value is greater than 0.25 |
| WM-4 | M47 M48 M13 R44 R48 RHM6 | If r value is greater than 0.3 |

Where, Tn = Average maximum temperature of nth week (°C)
Mn = Average minimum temperature of nth week (°C)
Rn = Rainfall during nth week (mm)
RHMn = Relative humidity (morning) nth week (%)
RHEn = Relative humidity (evening) nth week (%)

would then pass through a transfer function, which decided the strength of the out signal [11, 12]. Finally, the output signal is send through all the output connections to other neurons.

$$y_j = \int \{W_j \times X_j\} - \theta_j \tag{1}$$

The function f(x) is called as an activation function, the activation function enable a network to map any non-linear process. The most commonly used function is the sigmoidal function expressed as:

$$f(x) = \frac{1}{1 + e^{(-x)}} \tag{2}$$

The variables were selected according to the model WM-20, WM-11, WM-8 for developing and evaluating the ANN models. The ANN model architecture is a single layer feed forward network, which is one of the simplest neural network and has been successfully used the prediction of the nonlinear process [13, 14]. The number of hidden layer is one. The transfer function from input to hidden layer is Tan-Sigmoid Transfer Function (Tansig) and from hidden layer to output layer is Linear Transfer function (Purelin). The Back propagation training function has been selected, which is the most common and accurate as reported by many workers. The performance function for training and testing of networks used are Mean Squared Error (MSE). The various combinations of hidden nodes and training function were done to arrive at optimum combinations to give less error [15]. The network iterations (Epochs) were kept at 500. Architecture for ANN models shown in Table 2. The neural network utility file is edited in MATLAB (7.6 Version). The input variable selection, input data source file, network option, training function, setting for the data for training, validation, plotting the predicting values and saving the network is created and run in MATLAB software.

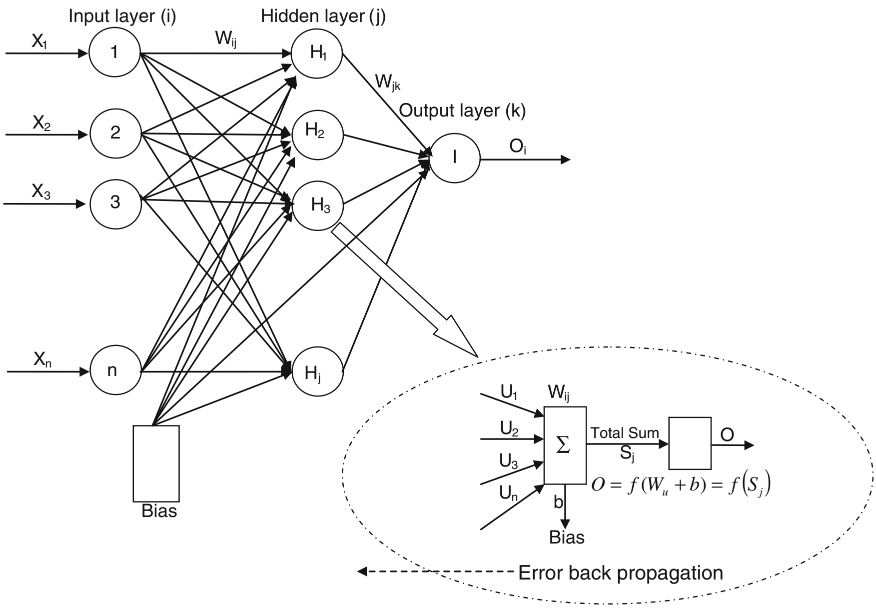



**Fig. 1** An artificial neuron showing its function

**Table 2** ANN algorithms, architecture and parameters used in ANN model

| Algorithm | Back-propagation-L.M |
|---|---|
| Training functions | Trainlm |
| Number of Neurons | 7 |
| Number of hidden layers | 1 |
| Scaling method | Normalization |
| Activation function of hidden layer | Tan-sigmoid |
| Activation function of output layer | Purelin |
| Number of Epochs | 500 |

### *3.1 Performance Indicators*

Correlation coefficient (R), Mean square error (MSE), Root mean square error (RMSE) and Mean Absolute error (MAE), were used as the model development parameters as well as the criteria for evaluation.

## 4 Result and Discussion

Initial ANN base model has been developed with Levenverg-Marquardt training algorithm with 7 neurons and a single hidden layer. Three models with 20,11,6 predictor variables have been developed.

**Table 3** Performance of various wheat ANN models

| Model | R | | MSE | | RMSE | | MSE | |
|---|---|---|---|---|---|---|---|---|
| | Trg | Val | Trg | Val | Trg | Val | Trg | Val |
| WM-20 | 0.87 | 0.37 | 2.69E−23 | 1.71 | 375 | 620 | 297 | 417 |
| WM-11 | 0.31 | 0.48 | 1.76E−10 | 1.61 | 576 | 719 | 423 | 333 |
| WM-6 | 0.87 | 0.51 | 1.76E−10 | 2.78 | 576 | 719 | 423 | 394 |

Training with 60 % of dataset and rest of data set use for validation
Trg = training, Val = validation

Performance of these three models has been summarized in Table 3. It can be observed that value of R during validation of the model WM-6 is much higher than the model WM-20 (0.3656) and the model WM-11(0.4782). However value R during training of the model WM-6 (0.8669) is slightly lower than the model WM-20 (0.8701). RMSE AND MAE for the model WM-6 are higher than the model WM-20 and WM-11, hence model WM-6 has been selected for further refinement.

### *4.1 Training Algorithms for Wheat Yield Model*

The WM-6 model was tested with different training algorithms. For developing the ANN based wheat yield model, performance of 12 training algorithms were evaluated. The model WM-6 was developed using Levenverg Marquardt Algorithm (trainlm).The best training algorithm in the hidden layer of ANN model can be determined by trial and error, at which the model performs best.

Table 4 indicates that the training algorithm “traincgf” resulted in model with highest value of correlation coefficient of 0.871 and 0.511 during training and validation respectively. Model performance indicator; MSE with scaled estimate and the target are lowest at 0.216 and 0.747 during training and validation respectively. RMSE has been worked out as 276.099 and 474.092; and MAE as 204.618 and 357.194 during training and validation respectively.

Hence the ANN wheat model with 6 input variables “mapstd” method of normalization, “traincgf” training algorithm at 7 neurons performed best amongst all twelve algorithms used for training.

### *4.2 Selection of Optimum Number of Neurons in the Hidden Layer for the Wheat Yield*

Increasing the number of neurons in the hidden layer, the network gets an over fit, that is the network have problem to generalize. Trial and error method is applied to determine the optimum number of neurons, at which the network performs best.

**Table 4** Performance of different training algorithm methods for ANN based wheat yield modeling

| S. No. | Algorithm | R | | MSE | | RMSE | | MAE | |
|---|---|---|---|---|---|---|---|---|---|
| | | Trg | Val | Trg | Val | Trg | Val | Trg | Val |
| 1 | Traingdx | 0.66 | 0.45 | 0.55 | 0.72 | 421.17 | 582.19 | 304.02 | 428.29 |
| 2 | Traingd | 0.60 | 0.46 | 0.71 | 0.64 | 494.88 | 575.68 | 383.70 | 332.62 |
| 3 | Trainscg | 0.61 | 0.51 | 0.37 | 0.98 | 443.00 | 527.16 | 341.45 | 402.46 |
| 4 | Trainrp | 0.46 | 0.58 | 0.43 | 0.70 | 555.22 | 692.13 | 411.44 | 308.82 |
| 5 | Trainoss | 0.76 | 0.43 | 0.25 | 1.50 | 366.85 | 617.04 | 276.11 | 519.77 |
| 6 | Trainlm | 0.87 | 0.51 | 0.00 | 2.78 | 284.74 | 487.40 | 225.02 | 394.29 |
| 7 | Traincgp | 0.78 | 0.43 | 0.16 | 1.24 | 354.98 | 519.38 | 252.37 | 408.01 |
| 8 | Traincgf | 0.87 | 0.52 | 0.22 | 0.75 | 276.10 | 474.09 | 204.62 | 357.19 |
| 9 | Traincgb | 0.79 | 0.49 | 0.25 | 0.70 | 340.53 | 495.93 | 250.19 | 385.58 |
| 10 | Trainbfg | 0.85 | 0.41 | 0.12 | 1.12 | 293.24 | 544.38 | 230.70 | 389.90 |
| 11 | Traingdm | 0.72 | 0.37 | 0.54 | 0.86 | 400.63 | 579.94 | 311.35 | 450.09 |
| 12 | Traingda | 0.27 | 0.55 | 1.21 | 0.80 | 734.11 | 831.59 | 576.55 | 374.83 |

Trg = training, Val = validation

**Table 5** Performance of neural network with different number of neurons of wheat yields ANN modeling

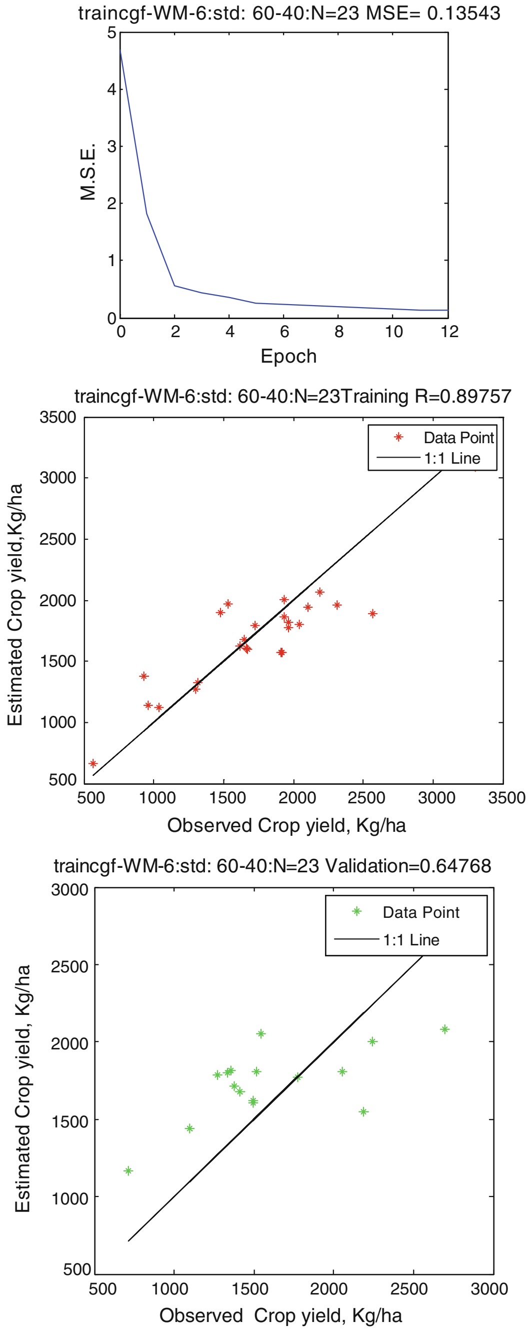
| S.No. | Model | R | | MSE | | RMSE | | MAE | |
|---|---|---|---|---|---|---|---|---|---|
| | | Trg | Val | Trg | Val | Trg | Val | Trg | Val |
| 1 | N1 | 0.61 | 0.45 | 0.61 | 1.14 | 450.85 | 621.76 | 313.90 | 453.95 |
| 2 | N2 | 0.58 | 0.48 | 0.47 | 1.47 | 502.79 | 633.69 | 371.39 | 380.97 |
| 3 | N3 | 0.41 | 0.52 | 0.57 | 0.98 | 527.97 | 699.83 | 378.88 | 404.95 |
| 4 | N5 | 0.61 | 0.38 | 0.29 | 1.36 | 486.05 | 685.67 | 389.70 | 402.42 |
| 5 | N7 | 0.87 | 0.52 | 0.22 | 0.75 | 276.10 | 474.09 | 204.62 | 357.19 |
| 6 | N9 | 0.80 | 0.49 | 0.22 | 0.76 | 338.78 | 490.62 | 265.58 | 372.12 |
| 7 | N11 | 0.83 | 0.42 | 0.25 | 1.11 | 315.18 | 559.36 | 214.76 | 459.84 |
| 8 | N15 | 0.61 | 0.25 | 0.26 | 1.40 | 450.49 | 643.62 | 357.09 | 485.02 |
| 9 | N17 | 0.40 | 0.46 | 0.29 | 1.20 | 592.64 | 568.81 | 469.57 | 425.80 |
| 10 | N19 | 0.47 | 0.47 | 0.29 | 0.90 | 537.86 | 645.50 | 478.41 | 373.93 |
| 11 | N20 | 0.64 | 0.45 | 0.28 | 0.91 | 434.56 | 567.38 | 319.66 | 392.12 |
| 12 | N23 | 0.90 | 0.65 | 0.14 | 0.71 | 259.07 | 438.68 | 196.09 | 352.53 |

Trg = training, Val = validation

Selection of optimum number of neurons is an essential part for wheat ANN model development. The model WM-6 with learning function "traincgf" and normalization function "mapstd" trained with 60 % of data has been evaluated for optimum number of neurons. Neurons in the hidden layer are varying from 1 to 25.

The comparison of performance parameters are presented in Table 5, it can be stated that the model W-6 is trained with "traincgf" algorithm, "mapstd" normalization function and 23 neurons have best performance (Fig. 2).

**Fig. 2** Performance of WM-6 model with "traincgf" training algorithm at 23 neurons for wheat yield estimation



# 5 Conclusions

Artificial Neural Network (ANN) model for estimation of crop yield was developed in the present work. The model has one input layer, one hidden layer and one output layer. Method normalizes the data "std" which transforms the data such that the mean is zero and standard deviation is unity. The input dataset for crop yield modeling includes weekly rainfall, maximum and minimum temperature, relative humidity (morning, evening) for 41 years (1969–2010). ANN models were developed in Neural Network Module of MATLAB (7.6 version, 2008). Model performance has been evaluated in terms of R, MSE, RMSE and MAE. The basic ANN architecture was optimized in terms of training algorithm, number of neurons in the hidden layer, input variables for training of the model. Twelve algorithms for training the neural network have been evaluated. Performance of the model was evaluated with number of neurons varying from 1 to 25 in the hidden layer.

From this study following salient points emerged. Highest value of correlation coefficient between the estimated and observed wheat yield was 0.898 and 0.648 during training and validation by ANN model. The ANN wheat model with "traincgf" algorithm, 23 numbers of neurons, 60 and 40 % length of record for training and validation with 6 input variables is found to be the best model for wheat yield estimation.

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