MAUSAM, **74**, 3 (July 2023), 825-832

MAUSAM

DOI : https://doi.org/10.54302/mausam.v74i3.174
Homepage: https://mausamjournal.imd.gov.in/index.php/MAUSAM

UDC No. 633 : 004.023.26

Weather based crop yield prediction using artificial neural networks : A comparative study with other approaches

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(*Received 6 April 2021, Accepted 24 January 2023*)

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सार — यह शोधपत्र पश्चिम बंगाल में जिला स्तर पर चावल की उपज का अनुमान लगाने के लिए समाश्रयण दृष्टिकोण और मल्टीलेयर परसेप्ट्रॉन (एमएलपी) कृत्रिम तंत्रिका नेटवर्क (एएनएन) दृष्टिकोण पर आधारित मौसम सूचकांकों की तुलना करने का प्रयास किया गया। मौसम परवर्ती के लिए मौसम सूचकांक, जैसे, न्यूनतम तापमान, अधिकतम तापमान, वर्षा और सापेक्ष आर्द्रता का उपयोग समय परिवर्ती के साथ-साथ उत्पादन परिवर्ती के रूप में चावल की उपज के साथ-साथ इनपुट परिवर्ती के रूप में किया जाता है। अध्ययन से पता चलता है कि एएनएन दृष्टिकोण फसल उपज अनुमान में मानक समाश्रयण दृष्टिकोण से बेहतर काम करता है। एक जिले को छोड़कर एमएलपी एएनएन दृष्टिकोण में पूर्वानुमान त्रुटि प्रतिशत लगातार 5% से कम पाई गई है।

ABSTRACT. This paper attempts to compare the weather indices based regression approach and Multilayer Perceptron (MLP) Artificial Neural Network (ANN) approach for rice yield prediction at district level of West Bengal. The weather indices for weather variables, *viz.*, minimum temperature, maximum temperature, rainfall, and relative humidity are used as input variables along with time variable *t* and yield of rice as output variable. The study reveals that the ANN approach works better than the standard regression approach in crop yield prediction. The prediction error percentages are found to be consistently less than 5% in MLP ANN approach except for one district.

Key words – Weather indices, Crop yield prediction, Regression, Artificial neural network, Prediction error percentage.

1. Introduction

Crop yield is a composite quantity which is influenced directly or indirectly by many factors during a cropping season. Among these, soil factors like soil pH, available nutrients, soil texture, organic matter content, soil-water relationship, the crop and cultivar, weather and climatic factors, including temperature, rainfall, humidity and light intensity are the major affecting factors. Except weather and climatic factors, all other factors can be altered to some extent. Weather variability between two crop seasons and also within a crop season brings source of variability in crop yield and thus the impact of weather and climate on the crop production becomes very important. Weather variables affect the crop growth and development differently during different stages of development. Hence the extent of influence of weather variables on crop yield depends on the magnitude as well as its distribution pattern of weather variables over the entire crop season. India being a country with a predominant agrarian economy and almost 70% of the population being directly or indirectly engaged in agricultural practices, the use of timely as well as reliable prediction of crop yield based on weather variables to minimize the adverse effects of weather on crop yield and for better planning and policy making relating to storage, procurement, distribution, pricing, marketing, export-import etc. is very important.

Crop yield prediction models have been developed for a number of years using statistical approaches like linear models (simple or multiple linear regression), discriminant function analysis, agro-meteorological models, predictions based on crop biometrical characters, etc. as well as crop growth simulation models. To mention a few, Jain *et al*. (1980) developed the pre-harvest model to forecast rice yield and Agarwal *et al*. (2001) developed forecasting model for wheat using weather indices.

Agarwal *et al*. (2012), Sisodiya *et al*. (2014), Pandey *et al*. (2015) developed weather based crop forecasting model using discriminant function analysis.

In the recent years with the evolution of advance computing technology, the techniques like Machine Learning and Artificial Intelligence are being increasingly used in different research areas. The Artificial Neural Network (ANN) falls under the umbrella of machine learning techniques. Artificial Neural Network is a multivariate, non-linear, non-parametric data driven self adaptive algorithmic method. The main advantage of neural network lies in its flexible function form. In ANN, for fitting a given data set specifying a particular model is not required. Recently many researchers have shown that ANN has a powerful and efficient pattern recognition and classification capabilities. Inspired by biological systems, ANN is able to learn from experience and update the solutions at different steps. Currently ANNs are being used for a wide variety of problems arising in many different fields of study like business, industry, science, agriculture and others.

The use of ANN and other machine learning techniques has immensely increased in agricultural research in recent years. A systematic review literature to see what research work has been done on the application of machine learning techniques in crop yield prediction has been made by Klomplenburg *et al*. (2020). They found that the important independent variables for crop yield prediction are temperature, rainfall and soil type, and the most used technique for crop yield modelling is Artificial Neural Networks. Laxmi and Kumar (2011), Droesch (2018), Niedbala (2019), Khaki and Wang (2019) are few of many to mention who have worked in crop yield prediction using artificial neural networks.

As stated above, ANN is data driven self-adaptive method that can capture the non-linearity in the data and the complex relationship between the weather variables and crop yield, which sometimes may not be captured or difficult to capture using other statistical approaches. In this paper, an attempt has been made to model the crop yield based on weather parameters using artificial neural networks. A comparative study of the performance of ANN with weather based regression approaches has also been made.

2. Materials and methods

2.1. *Data*

Rice is most dominant crop in India and West Bengal is the highest producer of rice (Agricultural Statistics at a glance, 2020) in India. In this paper the kharif rice yield data in the four districts with highest yield rate of rice in West Bengal have been used. The districts are Birbhum, Burdwan, Hooghly and Nadia. District-wise yearly yield data of the kharif rice has been collected from the released issues of yield estimates of Bureau of Applied Economics and Statistics (BAES), Department of Statistics and Programme Implementation, Government of West Bengal for 34 years from 1981-1982 to 2014-15.

Data on different weather variables for those districts mentioned here have been collected from NASA Power data access viewer (power.larc.nasa.gov/data-access-viewer) starting from 1981 to 2014. For this study, weather data on minimum temperature, maximum temperature, rainfall and relative humidity were considered. The daily data was first converted into weekly data as per standard meteorological weeks. The weather during pre-sowing period affects the field preparation, sowing and germination of the seed. The heavy rainfall or drought during this period can delay the sowing or severely damage the sown crop leading to affect crop establishment and ultimately crop yield. The weather data from pre-sowing period, *i.e*., 23rd standard meteorological week through to harvesting period, *i.e*., 41st standard meteorological week have been considered.

2.2. *Methodology*

In this study we have focused on modelling the crop yield based on weather variables through weather indices based regression models and artificial neural network models using Multilayer Perceptron (MLP) architecture with resilient back propagation algorithm.

2.2.1. *Weather Indices based regression models*

Let m denote the number of weeks in any particular crop season and p denote the number of weather variables taken in the study. Let X_{iw} (i = 1, 2, …, p; w = 1, 2, …, m) denote the value of i^{th} weather variable in w^{th} week and y_t denote the crop yield for the year t (t = 1,2,…,34). Since the influence of each weather variable on crop yield is different, the contribution of each weather variable is to be studied separately. Moreover, for a particular weather variable the influence of that variable for different weeks on crop yield are also significantly different. Hence using the weekly data of each weather variable, a weighted variable is constructed with respect to each weather variable for every year considered under study. The weights assigned to the weekly data of a particular weather variable are simple correlation coefficients obtained between the crop yield (adjusted for time trend) and weekly weather data of the i^{th} weather variable taken over the years. In particular, the weight associated with the m^{th} week of a weather variable will be the correlation between yield and m^{th} week data of that variable over the years. These weighted variables are termed as weather indices. The weather indices of a particular weather variable in a particular year which is basically the representative of weather variable value for that year obtained by combining the weekly influence of weather variable in the following manner

$$Z_{t(i)} = \sum_{w=1}^{m} r_{[y_t, X_{tw(i)}]} X_{tw(i)} / \sum_{w=1}^{m} r_{[y_t, X_{tw(i)}]}$$

In the similar lines the weather indices for interaction effects can also to be constructed. Here the weights are simple correlation coefficient between the crop yield (adjusted for time trend) and product of the i^{th} and i'^{th} weather variables in w^{th} week and over the years. The weather indices for interaction effects of weather variables (taken two at a time) in a particular year is defined as

$$Q_{t(ii')} = \sum_{w=1}^{m} r_{[y_t, X_{tw(ii')}]} X_{tw(i)} X_{tw(i')} / \sum_{w=1}^{m} r_{[y_t, X_{tw(ii')}]}$$

These weighted indices take care of weekly distribution of weather variables with reference to its relation with the crop yield. These indices and model was used by Jain *et al.* (1980) to forecast rice yield in Raipur district.

The pre harvest forecast models to be obtained by applying multiple regression technique by taking weather indices and time variable t as predictors. Stepwise regression analysis will be used for selecting significant variables. The regression model will be as follows:

$$y_t = a + \sum_{i=1}^{p} b_i Z_{t(i)} + \sum_{i \neq i'=1}^{p} b_{ii'} Q_{t(ii')+ct+\varepsilon}$$

2.2.2. *Multilayered Perceptron Artificial Neural Network models*

Multilayer feed forward neural network or multilayered perceptron (MLP) architecture is a very popular neural network architecture used for a wide variety of tasks including forecasting (Zhang *et al.*, 1998). This network consists of an input layer. The input layer is made of non-linear elements called neurons (alternatively called as nodes) which simply accept the predictor value. Successive layers of neurons receive input from the previous layers. The outputs of nodes in each layer are inputs to nodes in the succeeding layer. The last layer is called the output layer. Layers between the input and output layers are known as hidden layers. Each node in each hidden layer receives input values from the nodes of previous layer and processes it through an activation function or transfer function to produces a transformed output for the nodes in the next layer or output layer.MLP architecture can have a variable number of hidden layers with a variable number of neurons in each layer. A feed forward network is a fully connected network which consists of a series of fully connected layers that connect each neuron in one layer to each neuron in the other layer. A feed forward network has one-way flow and no cycles. Fig. 1 gives an example of a fully connected MLP with one hidden layer.

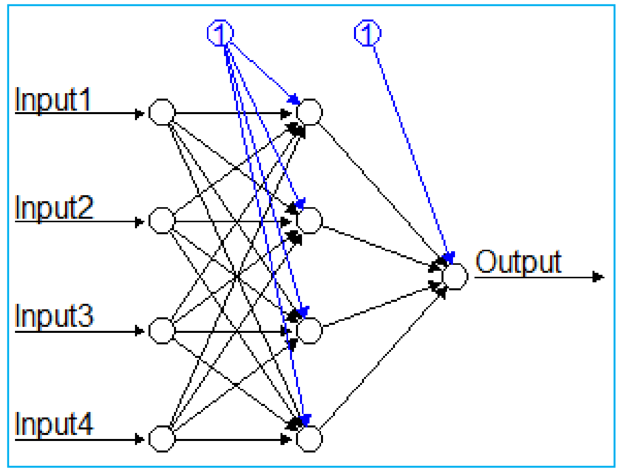

Fig. 1. A typical fully connected MLP with one hidden layer

For a causal relationship problem, the information given to input layer in an ANN are the predictor variables. The functional relationship estimated by the ANN can be written as :

$y = f(x_1, x_2,..., x_p)$, where $x_1, x_2,..., x_p$ are predictor variables and y is the response.

The output of j^{th} node in the neural network is given by :

$$\text{Output}_j = g\left(\theta_j + \sum_{i=1}^{p} w_{ij} x_i\right)$$

where g is a transfer or activation function, θ_j is the bias of the node j, $w_{1j}, \ldots, w_{pj}$ are weights of node j and x_i (i = 1,2,…,p) are the input variables. Thus the network has an interpretation of input-output model, with weights associated to each neuron and biases in each layer as free parameters of the model. These networks can model a function of high complexity in which the numbers of hidden layers, and the number of neurons in each layer, determine the degree of complexity of the function. In designing a MLP one must determine the number of input nodes, the number of hidden layers and nodes in each hidden layer and the number of output nodes. For causal relationship modelling, the numbers of input nodes are usually the number of input variables and the number of output nodes is the number of dependent variable considered in the study. The hidden layer and nodes play very significant role in the ANN modelling since the hidden layers and nodes allow neural networks to detect and also capture the features and patterns in the data to perform complicated nonlinear mapping between input and output variables. There is no solid theoretical basis for selecting these parameters till date, the most common way of determining the number of hidden layers and nodes is Trial and error method (Zhang *et al*., 1998).

The ANN modelling basically consists of training the network and then validating the trained network using the hold out data which were not used for training. In the training process the network produces it own output through the learning algorithm and tries to minimize the difference between its own output and desired output (target value). The minimization of difference is done by adjusting the weights of neurons and biases. This is called as the learning process of the network.

In this study, resilient back propagation (RPROP) algorithm (Riedmiller and Braun, 1993) have been used which is a faster and improved version of commonly used back propagation training algorithm. For back propagation algorithm, a free parameter called learning rate needs to be specified, since that will determine the magnitude of weight changes. It is well known that back propagation algorithm suffers the problems of slow convergence, inefficiency and lack of robustness since it is very sensitive with respect to the choice of learning rate. Smaller learning rates make the learning process slow while the larger learning rates may bring network oscillation in the weight space. Resilient back propagation algorithm works similarly to back propagation except it doesn't require specifying any free parameter value. The RPROP algorithm considers only the signs of gradient to be optimized and not their absolute values for weight updates. Also instead of using a single learning rate (as in back propagation) for all weights and biases, RPROP maintains separate weight deltas for weight of each neuron and bias, and adapts these weight deltas during training.

In artificial neural network training, the activation function also plays a very critical role since that determines the relationship between input and outputs of a node and also introduces non-linearity in the model which is the core of ANNs. The sigmoid (logistic) function is the most popular activation function in neural networks. The sigmoid (logistic) function is given by $f(x) = 1/1 + e^{-x}$. In this study, neural network models with 1 or 2 hidden layers and different number of neurons (3, 4, 5) in a hidden layer with logistic function as activation function have been considered. For output nodes linear activation function has been used as suggested by Rumelhart *et al*. (1995). Before training the ANNs, the dataset was scaled in [0, 1] scale. The best network was selected by considering the lowest error measures like root mean squared error (RMSE) and mean absolute percentage error (MAPE).

The analyses in this study have been carried out using R statistical package (version 3.6.2, 2019). For regression analyses *lm* () function under *stats* package has been used along with *ols_step_both_p*() function under *olsrr* package for stepwise variable selection. For neural network analyses, *neuralnet*()function under *neuralnet* package have been used.

2.3. *Model selection Criteria*

2.3.1. *Root mean square error (RMSE)*

Root Mean Square Error (RMSE) is the standard deviation of the prediction errors. It is given by :

$$\text{RMSE} = \sqrt{\frac{1}{k}\sum_{i=1}^{k}\left(Y_i - \hat{Y}_i\right)^2}$$

where Y_i and $\hat{Y}_i$ are the observed and predicted values of yield respectively and k is the number of observations in the validation group.

2.3.2. *Mean absolute percentage error (MAPE)*

The mean absolute percentage error (MAPE), is a measure of prediction accuracy of a forecasting method. It usually expresses accuracy as a percentage, and is defined by the formula:

$$\text{MAPE} = \frac{100}{k} * \sum_{t=1}^{k}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right|$$

where Y_i and $\hat{Y}_i$ are the observed and predicted values of yield respectively and k is the number of observations in the validation group.

TABLE 1

The estimated regression models for different districts using weather indices

Districts	Model	Adjusted R^2	*p*-value
Birbhum	$\hat{y} = -44.362 + 2.473 Z_2 - 0.002 Q_{34} + 0.495 t$	0.92	0.0000
Burdwan	$\hat{y} = 22.581 - 0.022 Q_{13} + 0.475 t$	0.84	0.0000
Hooghly	$\hat{y} = 16.744 - 0.159 Z_3 - 0.468 t$	0.91	0.0000
Nadia	$\hat{y} = -22.992 + 1.273 Z_1 - 0.005 Q_{34} + 0.433 t$	0.80	0.0000

TABLE 2

RMSE and MAPE of various developed models and their structures

Districts	Methodology	Model structure	RMSE	MAPE	Selected models
Birbhum	Neural network models	2N 1L	0.3961	1.1498	
		3N 1L	**0.2872**	**0.9226**	**Best Model**
		4N 1L	0.6067	1.6559	
		3N:2N 2L	0.7600	2.0429	
	WI based model	$\hat{y} = -44.362 + 2.473 Z_2 - 0.002 Q_{34} + 0.495 t$	0.6025	1.6832	
Burdwan	Neural network models	2N 1L	0.7376	2.0739	
		3N 1L	0.7000	1.9582	
		4N 1L	**0.6382**	**2.0033**	**Best Model**
		3N:2N 2L	0.8956	2.6425	
	WI based model	$\hat{y} = 22.581 - 0.022 Q_{13} + 0.475 t$	0.8331	2.4068	
Hooghly	Neural network models	2N 1L	0.7631	1.9806	
		3N 1L	**0.6492**	**1.7829**	**Best Model**
		4N 1L	0.7265	2.3205	
		3N:2N 2L	0.8454	1.9065	
	WI based model	$\hat{y} = 16.744 - 0.159 Z_3 - 0.468 t$	1.5414	4.4931	
Nadia	Neural network models	2N 1L	1.9662	6.7576	
		3N 1L	**1.6591**	**5.3429**	**Best Model**
		4N 1L	1.8490	6.2225	
		3N:2N 2L	2.7083	7.6351	
	WI based model	$\hat{y} = -22.992 + 1.273 Z_1 - 0.005 Q_{34} + 0.433 t$	1.9256	6.7924	

2.3.3. *Prediction error (%)*

The prediction error % using actual yield (Y_i) and predicted yield ($\hat{Y}_i$) was computed using below formula.

$$\text{Prediction error \%} = \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times 100$$

3. Results and discussion

In this study, the weather variables are used as weather indices. The weather indices for each weather variable have been developed in Section 2.2.1. A total of 10 indices have been developed (4 for individual effects and 6 for interaction effects). These weather indices along with time variable *t* have been used as predictor or input variables for the model development. The yield

TABLE 3

The actual yield, predicted yield and their corresponding prediction errors for each district

Districts	Year	Actual yield	ANN model		Regression model	
			Predicted yield	Prediction error %	Predicted yield	Prediction error %
Birbhum	2011-12	28.824	28.453	1.30	27.838	3.54
	2012-13	28.058	27.851	0.74	28.331	-0.96
	2013-14	33.034	33.303	-0.81	33.178	-0.44
	2014-15	32.617	32.895	-0.85	33.237	-1.87
Burdwan	2011-12	30.058	29.441	2.10	30.620	-1.83
	2012-13	30.922	31.564	-2.03	32.310	-4.29
	2013-14	31.605	30.799	2.62	32.088	-1.51
	2014-15	31.515	31.094	1.35	32.064	-1.71
Hooghly	2011-12	28.372	28.086	1.02	30.637	-7.39
	2012-13	28.267	28.782	-1.79	30.223	-6.47
	2013-14	27.816	27.665	0.55	28.544	-2.55
	2014-15	30.536	29.389	3.90	30.675	-0.45
Nadia	2011-12	26.766	26.268	1.89	25.437	5.23
	2012-13	22.808	21.975	3.79	24.410	-6.56
	2013-14	27.722	25.593	8.32	26.340	5.25
	2014-15	28.747	26.394	8.92	25.816	11.35

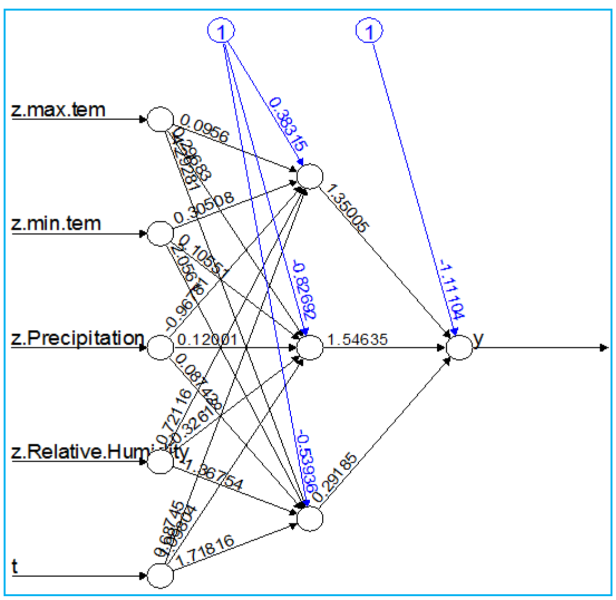

Fig. 2. Best selected Neural Network for Birbhum district

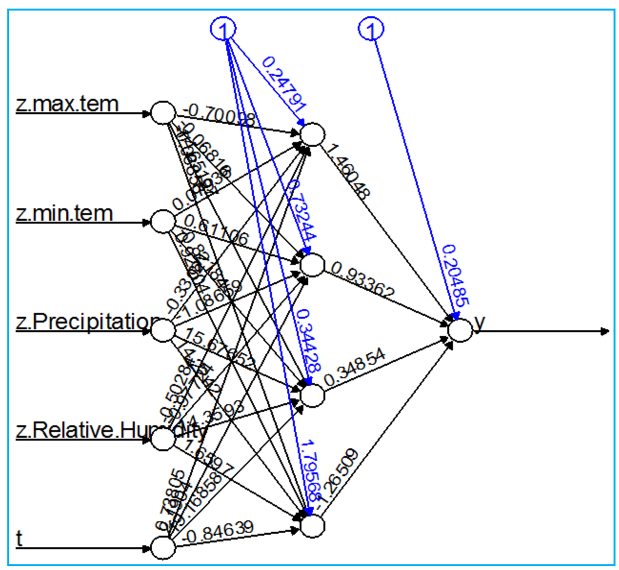

Fig. 3. Best selected Neural Network for Burdwan district

(quintal/ha.) of the rice crop has been taken as the response variable. The entire dataset has been divided into two distinct groups, *viz*., training group and validation groups. The training group consists of 30 years' data while the validation group consists of 4 years' data. The models have been developed for four districts considered in the study, *viz*., Birbhum, Burdwan, Hooghly and Nadia of West Bengal, India.

3.1. *Weather indices based regression model*

In the multiple regression model development, both individual and interaction effect indices (weighted and un-weighted all) along with time variable *t* have been used as predictor variables and the data on rice crop yield have been used as response variable. Stepwise variable selection method has been used to obtain the final model.

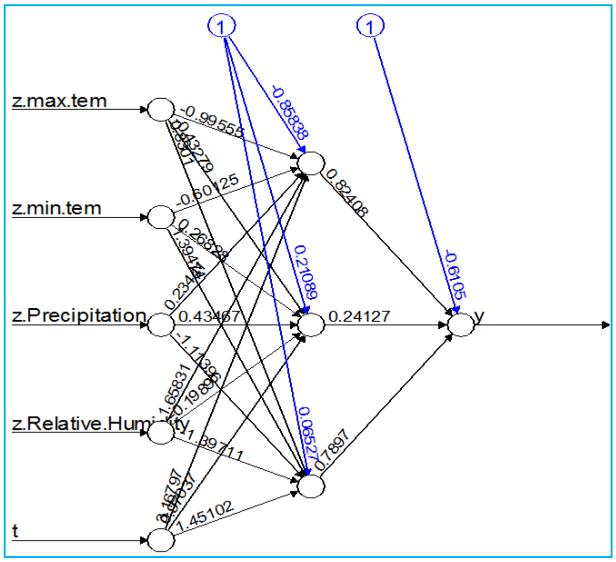

Fig. 4. Best selected Neural Network for Hooghly district

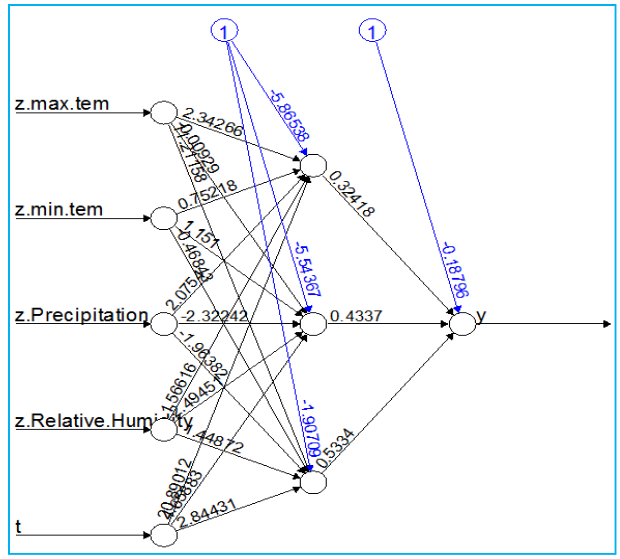

Fig. 5. Best selected Neural Network for Nadia district

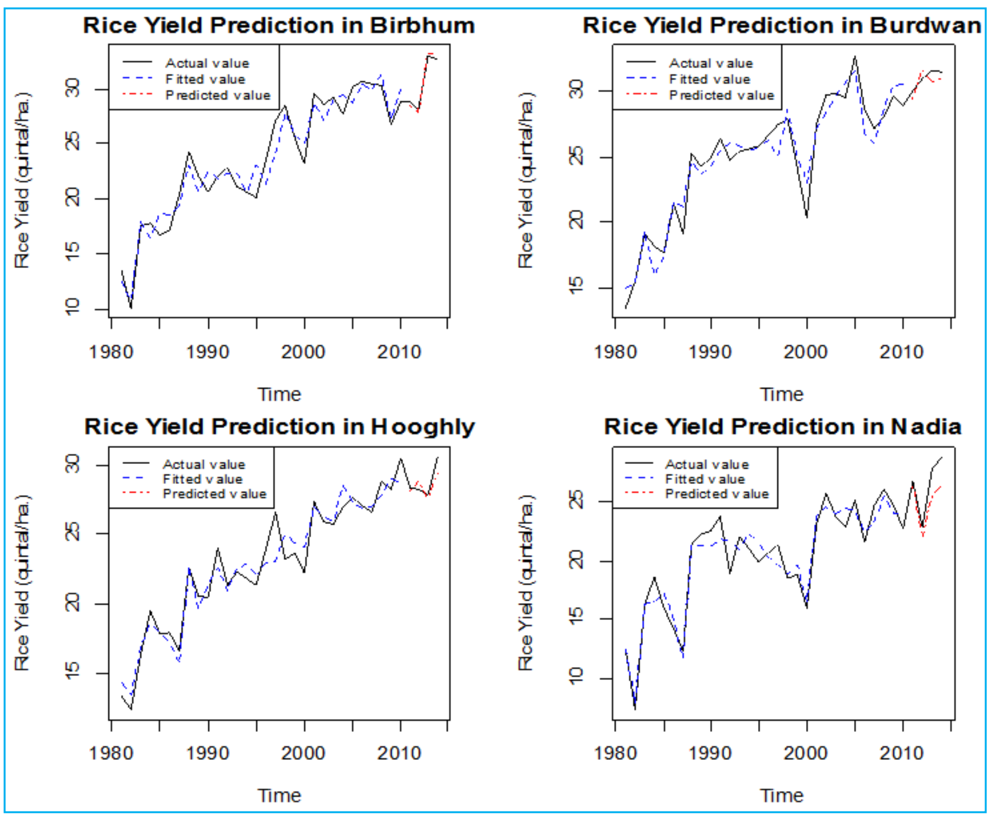

Fig. 6. Actual, Fitted and Predicted values of Rice yield in Birbhum, Burdwan, Hooghly and Nadia districts

The estimated models with significant variables have been obtained and are presented in Table 1.

From Table 1, it has been found that weather indices based regression models provides a very good fit for the data of all 4 districts. The R^2 for fitted regression models are greater than 0.80 for all 4 districts. The *p*-values for all models are less than 0.001 which suggests that the models fit the data very well.

3.2. *Models based on MLP Artificial Neural Networks*

In neural network modelling, weather indices only for individual variables have been used as input variables since the network can acquire the interaction patterns (if any) during learning of network. Various neural network models with different combination of number of hidden layers and number of neurons in a hidden layer have been developed. The RMSE and MAPE for various developed models have been obtained using the hold out dataset. The combinations of some selected models along with their error measures are reported in the Table 2.

From Table 2, based on lowest RMSE and MAPE values, the Neural Network models are found to be the best for all four districts considering the fact that the structures for ANNs are different in all four districts. The best selected neural networks are presented by Figs. 2-5 for Birbhum, Burdwan, Hooghly and Nadia districts, respectively.

From the best selected models, the predicted yield for the duration of validation group data and their corresponding prediction errors are obtained and presented in Table 3.

From Table 3, it is evident that the prediction error percentages are consistently less 5% for the validation period in MLP ANN approach; only for Nadia district it has reached 9%. The graphical representation of actual, fitted and predicted values of rice yield for all the districts considered in the study is shown in Fig. 6.

4. Conclusion

This article has made an attempt to perform a comparative study between weighted regression approach and artificial neural network approach for crop yield prediction. The study shows that the performance of artificial neural network is consistently better than the weather indices based regression models for crop yield prediction based on RMSE and MAPE. The prediction error percentages are found to be consistently less than 5% in MLP ANN approach except for Nadia district. The best selected model can be used to obtain a reliable forecast of crop yield at any time before harvesting (6-8 weeks before) using the weather data till the time of forecast.

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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