Original Research Article

Comparison between different Mustard yield prediction models developed using various techniques for Udaipur region of Rajasthan

ABSTRACT

The present research was conducted to develop and compare mustard yield prediction models using SPSS regression, Artificial Neural Network (ANN) and Autoregressive Moving Average (ARIMA) model. Mustard crop is one of the major *rabi* crop of India with Rajasthan as the leading mustard producing state. In this study eight different weather parameters were used to develop mustard yield prediction model, using different yield prediction techniques. Weather and yield data from year 1999 to 2015 were utilised for calibration and year 2016 to 2018 for validation. Three different algorithms were used in ANN to predict mustard yield. Time series model (ARIMA) is another technique used in this study to forecast mustard yield for Udaipur district. In order to analyse and compare error(s) in developed models and to compare simulated and actual/observed yield, different error indices like root mean square error (RMSE), standardized root mean square error (SRMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and D Index were considered.

Keywords: yield, temperature, SPSS, ANN, ARIMA, indices, prediction, mustard

INTRODUCTION

Prediction of various crops like rice, wheat, mustard, soybean have been a foremost matter of concern in the field of research based on Agriculture meteorology. Mustard crop is the second most important widely cultivated oil seed crop grown in India after groundnut. It is a *rabi* season crop cultivated in both irrigated as well as rainfed conditions (Shekhawat *et al.,* 2012). Around 11% of the world's total production of mustard seed is from India, holding fourth highest producer in the world. Rajasthan contributes around 43% of the total mustard seed production in India (Kumrawat *et al.,* 2018). It is therefore important to study and do research regarding mustard yield prediction under local weather condition. Major oilseeds crops grown in Udaipur are mustard, soybean, sesame and groundnut (Meena, 2016).

In India, mustard is generally sown in the month of September-October and harvested in the month of February-March in locations with well drained sandy loam soil (Singh *et al.,* 2017).

Crop simulation model based on weather provides detail description regarding impact of weather on crop yield on various growth stages and plays a vital role in providing area specific yield forecast under local weather condition. It is also very important to evaluate the performance and accuracy of the developed model using different metrics like RMSE, MAE and MAPE (Joshua *et al.,* 2021).

ANN model is a mathematical model which is comparatively complex having many connecting neurons for processing data. ANN model has three layers namely input, output and hidden layer having various sets of weights which is tuned by different algorithms. Different activation functions (tansig, purelin, log) present in ANN helps in converting the weighted inputs into the output activation (**Kumar *et al.,* 2014**). In this study, three algorithms namely Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugated Gradient (SCG) were used in ANN to predict mustard yield. Other technique used to predict mustard yield is by using time series ARIMA model. This model is important to forecast univariate time series data (**Tripathi *et al.,* 2014**). Factors like autoregressive (p), differencing (d) and moving average (q) were identified based on the significant spikes in partial autocorrelation function (PACF) and autocorrelation function (ACF) plots of mustard yield. This study aims to develop mustard yield prediction model for Udaipur, using three different models like SPSS, ANN and ARIMA. In order to analyse error(s) in developed models and to compare simulated and actual/observed yield, different error indices like root mean square error (RMSE), standardized root mean square error (SRMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and D Index were calculated. Study based on cause of yield reduction, yield prediction and risk associated with the same should mainly contribute the outcomes in terms of environment, health and socio-economic aspects like employment, income and economic growth (Bernardi *et al.,* 2016).

MATERIALS AND METHOD

The present study was carried out for Udaipur district of Rajasthan having lat 24.5854°N and long 73.7125°E. The weekly weather data i.e SMW 40 to 13 from 1999 to 2018 was collected from ICAR- Central Research Institute of Dry Land Agriculture (ICAR-CRIDA, AICRPAM unit) situated in Hyderabad. The yield data of Mustard for 20 years (1999 to 2018) was taken from Directorate of Economics and Statistics, Government of India.

Development of regression model using PCA technique

In a large dataset, in order to reduce the dimensionality of the variables in an interpretable way PCA technique is used since long time. The main idea of Principle component analysis is to reduce the dimensionality of a dataset, while preserving as much 'variability' (i.e. statistical information) as possible. This technique has sometimes been reinvented, in many different disciplines. It is a statistical technique and hence much of its development has been by statisticians. This means that 'preserving as much variability as possible' translates into finding new variables that are linear functions of those in the original dataset that successively maximize variance and that are uncorrelated with each other. Finding such new variables, the principal components scores (PCs), gives the variation details in the form of an eigenvalue/eigenvector problem (Jolliffe and Cadima, 2016). In this study, PCA technique was undertaken to find the PC scores using dimension reduction and factor analysis method.

In the current study, weekly weather data of 17 years (1999-2015) i.e. from SMW 40 to SMW 13 has been taken to develop the mustard yield forecast model and weekly weather data of same SMWs were taken to validate the model from 2016 to 2018. Therefore the PCA technique has been employed to determine the most prominent variables, which are then used in multiple regression analysis for development of yield forecasting models of Mustard crop. Different steps involved in PCA method is described in Fig. 1, where 19 components were extracted as Principle components and therefore principle components scores or PC scores from PC1 to PC19 were calculated for 20 years (1999 to 2018). Scree plot data obtained after PCA also indicated that out of all the components, 19 components are responsible for creating variation of 99.36% in mustard yield. Therefore, out of total 208 components in PCA, we used only 19 PC scores and the variability of those 19 PC score was 99.36%. After computation of those 19 PC scores (PC1 to PC19) along with de-trended yield were taken as independent variables and actual yield of mustard was taken as dependent variable in SPSS. In this study, 26 weeks weather variable is used therefore, the multi-linear equation to develop model as below in equation 1:

$$Y= \beta_0 + \beta_1 x_1+\beta_2 x_2+\ldots\ldots\ldots\beta_n x_n \qquad (1)$$

Where, Y is dependent variable, β_1 β_2 β_n are coefficients

β_0 is constant and x_1 x_2 x_n are the independent variables

Artificial Neural Network: ANN model consist of input, hidden and out layers which are connected with weights. Hidden layer consist of different algorithms which are trained to get the predicted value or output with the help of activation function. Weather data for training or calibration (from year 1999 to 2015), validation (2015 to 2018) and yield or target data was imported in workspace window of ANN as input data. In Hidden layer, network was created using feed forward backdrop network type, tansig activation function and three different algorithms like Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugated Gradient (SCG). In this layer, all the raw data received from input layer is processed with the help of interconnecting nodes using above mentioned algorithms and activation transfer function like tansig. Each node accepts the data from the previous node and therefore, calculates the sum of all the weighted inputs which is given in equation 2:

$$Y = \sum xw + Af \qquad (2)$$

Where Y is the predicted output or yield

X is the input, w is the weights and

Af is the activation function

Training process or simulation is continued in the neural network training window till any of the progress values like number of iterations, validation checks, performance and gradient value reach the maximum limit. As soon as the training progress completes, correlation coefficients, validation plots was generated at different epochs which determines the performance of ANN trained model on the basis of mean squared error (MSE) and coefficient of correlation. After completion of training and validation in hidden layer, output as predicted yield was computed and exported in the data manager window of ANN which is then transferred in the output window or the output layer of ANN.

ANN model has various nodes in the form of weights which transfers the raw input and the target data to get the forecast. In this study, weather variables were imported in the input layer and actual mustard yield were taken as the target data to achieve the goal of developing mustard yield prediction model using ANN. Three different algorithms namely Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugated Gradient (SCG) and tansig activation function were taken in the hidden layer to predict mustard yield. Weather and mustard yield data from harvesting year 1999 to 2015 was taken for training or calibration and from year 2016 to 2018 for validation. Study conducted by Amaratunga *et al.*, 2020 also used ANN model to predict paddy yield using different training algorithms.

Forecasting model using ARIMA: As ARIMA model is a univariate time series model, therefore in this study, mustard yield data of 20 years (1999 to 2018) is used for analysis. To evaluate the value of p and q, it is important to analyse the auto-correlation factor (ACF) and partial auto correlation factor (PACF) graphs which is generated after performing the differencing process and making the data stationary. ACF graph plot gives the description regarding the number of significant spikes of data for moving average (MA) model and is denoted as q. Whereas, partial autocorrelation (PACF) graph indicates number of significant spikes for auto regressive (AR) model denoted as p at different lag intervals. Hence, ARIMA (p,d,q) values was observed and analysed to develop model and forecast yield from 1999 to 2018. Yield data from 1999 to 2015 was used for calibration to forecast yield from year 2016 to 2018. In model summary of ARIMA, statistical details regarding stationary R square, root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and normalized bayesian information criterion (Bic) were also analysed. Less value of Bic indicates better performance of model developed by ARIMA technique.

Performance of models

The performance of the developed model using all the three techniques (regression, ANN and ARIMA) was evaluated oe tested using different error indices like root mean square error (RMSE), normalised root mean square error (NRMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and D Index using following formulae:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}}$$

$$\mathrm{NRMSE} = \frac{\mathbf{RMSE}}{\mathbf{Average\ of\ actual\ yield\ of\ mustard\ (Oavg)}}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|S_i - O_i|}{n}$$

$$\mathrm{MAPE} = (1/n) * \Sigma(|O_i - S_i| / |O_i|) * 100$$

$$D = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - O_{avg}| + |O_i - O_{avg}|)^2}$$

Where S_i is simulated or predicted yield, O_i is actual yield and n is the number of observation

RESULTS AND DISCUSSION

As mustard is one of the important oilseed crop of India which is grown mainly in *rabi* season, therefore research based on its cultivation, crop-weather correlation, yield forecast, net sown area, decision making to avoid yield loss, market value has a great significance. This study has highlighted on developing models to predict mustard yield of the study area using three different modeling techniques like multiple regression (SPSS), artificial neural network (ANN) and autoregressive integrated moving average model (ARIMA).

Development of Regression model using SPSS: Stepwise multiple regression technique was used to develop model for prediction of mustard yield for Udaipur using different weather parameters. From the scree plot graph in Fig 2, it was observed that the arm of the data with eigen values become flat after component number 19. This indicates that total number of principle component was 19 and thus the PC scores computed was (PC1 to PC19). After principle component analysis, in order to construct the regression model, these PC scores with detrended yield of mustard were used as independent variables and actual yield was taken as dependent variable to develop the regression model by calibration from 1999 to 2015.

Table 1 shows the constant and the coefficient values received after multiple regression analysis in spss to predict mustard yield. Three models were formed in regression model during calibration where PC scores (PC3 and PC15) has significance in mustard yield forecast along with the detrended yield. The constant and the coefficient values obtained in table 1 after calibration was incorporated in multiple regression equation (1) to develop model for validation for the next three years from year (2016 to 2018) and therefore model was developed and mustard yield was predicted using SPSS from year 1999 to 2018. Predicted yield of mustard using regression model along with actual yield, dtrend, pc scores for harvest year 1999 to 2018 has been given in table 2.

Artificial Neural Network: Algorithm having the coefficient of correlation value close to 1 and lowest value of mean square error (MSE) and number of epochs is considered best for yield prediction from ANN model. Table 3 and fig 3 to 5 shows that the coefficient of correlation (R) between weather variables and mustard yield using SCG algorithm shows better result as the R value using SCG algorithm varies from 0.86 to 0.91 which is close to 1. Table 4 shows the validation performance of SCG was better than LM and BR algorithm as the mean square error (0.005303) and epoch value (0) using SCG was less.

A similar kind of study was conducted by Amaratunga *et al.,* 2020 using three different algorithms (LM, BR and SCG) of ANN model taken to predict paddy yield at different locations of Sri Lanka. The results showed that LM algorithm outperformed the other two algorithms and gave the better results with correlation coefficient closer to 1, less epoch value and mean square error. However, with reference to the number of epochs, both LM and SCG have performed well but overall LM algorithm gave the best prediction for paddy.

Development of yield prediction model using ARIMA: In figure 6, PACF graph shows that two spikes at lag 1 and 2 are significant, therefore 'p' value identified from the PACF (autoregressive) graph was 2. Similarly in fig 7, ACF graph shows only one significant spikes at lag 1, which denotes that the 'q' value identified from ACF (moving average) graph was 1. Difference of 2 level is considered ideal for making the mustard yield data stationary. Therefore, the final evaluated p,d,q value was ARIMA (2,2,1). The same model has been used for calibration (1999 to 2015) as well as validation (2016 to 2018). Table 7 summarises the statistical output from the developed model which had shown the normalised BIC (2.5333), RMSE (2.707), MAPE (15.87%) and MAE (1.749) values.

Performance evaluation of models using different error indices:

The ranking of the yield predicting models on the basis of different error indices has been shown in Table 7, for Udaipur. Inter-comparison was performed using different formula of statistical indices for evaluating the performance of models to predict mustard yield. It has been observed that the regression model (SPSS) has the least error value in all the statistical indices (RMSE, NRMSE, MAPE, MAE) as compared to other two models. According to statistical error indices, table 7 shows that SPSS regression model has the least RMSE value which is 0.1. Also as far as error percentage is concern, unlike ANN and ARIMA model, SPSS regression model showed very less error percentage (1.3 to 1.6%) whereas ANN model has 12 to 48% error and ARIMA model has shown 8.4% error in predicting mustard yield. D Index value varies from 0 to 1. For best performance of model, the D Index value should be close to 1. As shown in table 7, D index value of SPSS is close to 1 (0.99) whereas that of ANN (0.1 to 0.4) and ARIMA (0.3) which is nowhere close to 1, this clearly indicated that the performance of SPSS model was far better than ANN and ARIMA model to predict mustard yield for Udaipur region. Also there was no over fitting of model in spss after performing PCA analysis, which was used to reduce the dimensionality of large set of weather variables while retaining well defined amount of variability in the original data to predict mustard yield. The principle components evaluated in spss have eigen values always more than one, thus it helps to study and analyse the major components responsible to predict crop yield and reduces the chances of multicollinearity in independent weather variables.

Similar kind of analysis was observed in study by Sathees Kumar and Mayur Shitap 2020, where stepwise regression model and ARIMA time series model was taken to predict groundnut yield in Junagadh district of Gujarat using weekly weather data. The results showed that stepwise regression method gave better result than ARIMA model as the approach using week wise weather data and year wise groundnut yield data in stepwise regression model like spss helped to avoid the consequences due to multicollinearity. Whereas ARIMA model is a univariate model and hence does not consider multicollinearity problem of independent variables at greater extent. Also the statistical error values of RMSE and MAE in spss was less than ARIMA model.

Aravind et al., 2022 also conducted study on the performance evaluation for wheat yield prediction using PCA- stepwise multiple linear regression (SMLR), ANN and other techniques. The results showed that out of five regions of study area, in three regions (Ludhiana, Amritsar and IARI- New Delhi) the prediction of wheat using ANN during validation showed comparatively more error due to over fitting than validation results using spss. Whereas in three regions (Ludhiana, Amritsar and Patiala) results showed that wheat yield prediction during calibration with ANN model has more error than spss.

On the contrary Bagheri et al., 2014 conducted study in Iran on yield prediction of lentil using ANN and multiple regression model. The result in this study concluded that ANN model prediction for lentil productivity was more accurate than regression model.

CONCLUSION

Three different modelling techniques like SPSS, ANN and ARIMA was used in this study to develop mustard yield prediction model for 20 years (1999 to 2018) for Udaipur district of Rajasthan. The main objective of this study aimed at developing best model to forecast mustard yield for Udaipur using weather variables like maximum, minimum temperature, morning and evening relative humidity, windspeed, rainfall, sunshine and evaporation. Results showed that out of all the three modeling techniques, regression method of developing mustard yield prediction for Udaipur region using SPSS was best than ANN and ARIMA model. Also the error indices showed that SPSS technique has minimum error and D index value close to one.

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Table 1. Constant and coefficient from regression model SPSS

Model		Unstandardized Coefficients	
		B	Std. Error
1	(Constant)	10.383	.017
	Dtrend	1.000	.010
2	(Constant)	10.386	.013
	Dtrend	1.000	.007
	PC3	-.013	.004
3	(Constant)	10.382	.010
	Dtrend	1.000	.006
	PC3	-.013	.003
	PC15	.022	.007

Table 2. Actual yield, pc scores, dtrend and predicted yield from SPSS regression model

			PC Scores		Predicted yield (q/ha)		
Harvested Year	Actual yield (q/ha)	dtrend	PC3	PC15	Model 1	Model 2	Model 3
1999	9.62	-0.65	-2.09	-2.19	9.73	9.76	9.71
2000	9.59	-0.70	4.39	-1.09	9.68	9.63	9.60
2001	9.28	-1.02	2.91	-3.25	9.37	9.33	9.26
2002	10.56	0.25	6.89	1.22	10.63	10.54	10.57
2003	9.73	-0.60	3.92	0.94	9.78	9.73	9.75
2004	13.06	2.72	3.27	-0.67	13.10	13.06	13.05
2005	11.29	0.93	1.18	0.97	11.32	11.31	11.32
2006	11.99	1.62	1.45	0.17	12.00	11.99	11.99
2007	9.1	-1.28	1.70	-0.36	9.10	9.08	9.07
2008	10.1	-0.30	-2.90	0.48	10.09	10.13	10.13
2009	8.18	-2.23	2.43	3.63	8.16	8.13	8.20
2010	8.91	-1.51	-0.27	-0.59	8.87	8.88	8.86
2011	15.6	5.16	-1.58	0.67	15.54	15.57	15.58
2012	10.01	-0.44	-7.43	0.23	9.94	10.04	10.04
2013	10.15	-0.31	-4.21	1.07	10.07	10.13	10.14
2014	10.48	0.00	-3.62	0.98	10.38	10.43	10.45
2015	8.87	-1.62	-2.74	0.45	8.76	8.80	8.80
2016	7.93	-2.57	-0.78	-2.47	7.81	7.83	7.77
2017	9.86	-0.66	-1.65	-1.83	9.72	9.75	9.70
2018	9.39	-1.14	-0.89	1.63	9.25	9.26	9.29

Table 3. Correlation coefficient values using three different algorithms in ANN model in calibration

		Correlation coefficient			
Study area	ANN Algorithms	Training	Validation	Testing	All
Udaipur	LM	0.6368	0.99619	0.85335	0.6757
	BR	0.88174	0.80956	0.78461	0.80666
	SCG	0.91431	0.86706	0.9476	0.8979

Table 4. Validation performance of predicted yield using ANN model

Study area	ANN Algorithms	MSE	Number of epochs
Udaipur	LM	0.19344	0
	BR	2.5789	20
	SCG	0.005303	0

Table 6. Statistical values from ARIMA model

ARIMA model	Model Fit statistics					
	Stationary R-squared	R-squared	RMSE	MAPE	MAE	Normalized BIC
Model 1	.727	-.743	2.707	15.875	1.749	2.533

Table 7. Inter-comparison of validated data of models

Modeling techniques		Statistical Indices				
		RMSE	NRMSE	MAPE	MAE	D Index
SPSS	Model 1	0.137	0.015	1.51	0.137	0.9
	Model 2	0.121	0.013	1.33	0.120	0.9
	Model 3	0.146	0.016	1.61	0.143	0.9
ANN	LM	4.59	0.51	48.13	4.22	0.11
	BR	1.33	0.15	12.40	1.03	0.46
	SCG	3.98	0.44	41.28	3.66	0.13
ARIMA	ARIMA (2,2,1)	1.0085	0.1112	8.400	0.6922	0.39

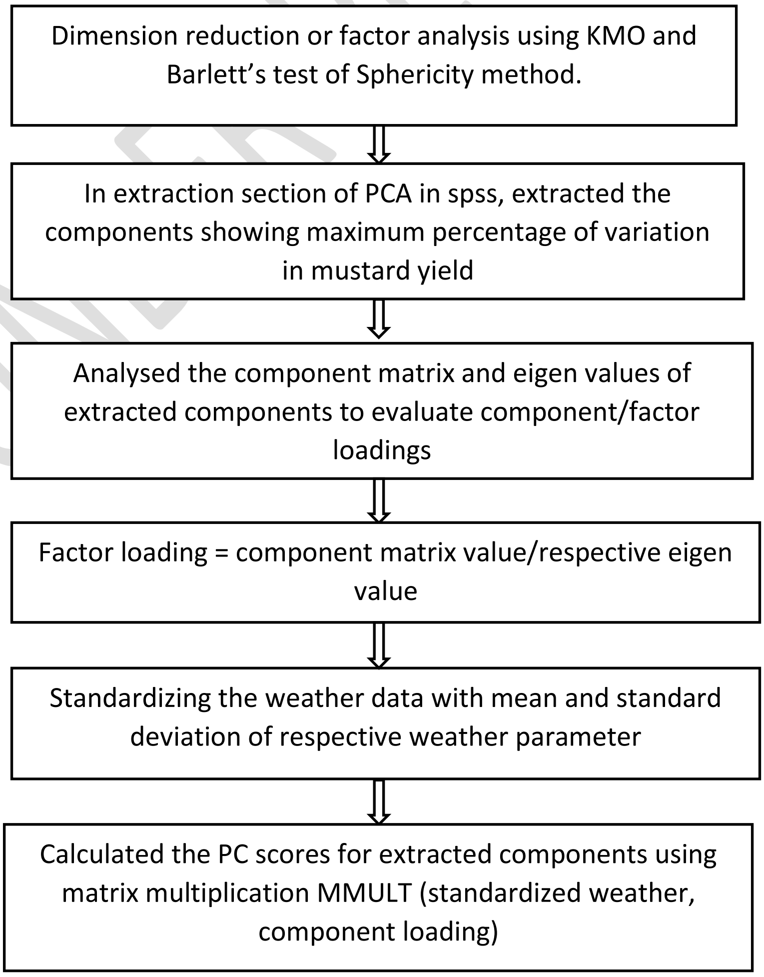

Fig.1 Principle component analysis in SPSS

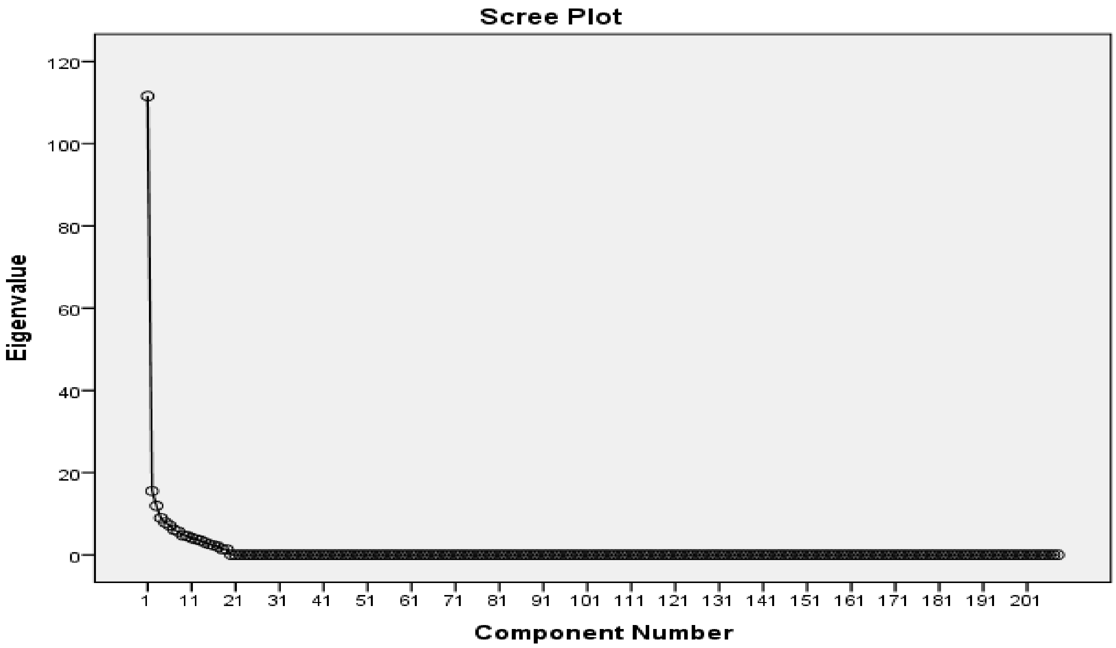

Fig 2. Scree plot obtained from PCA in SPSS

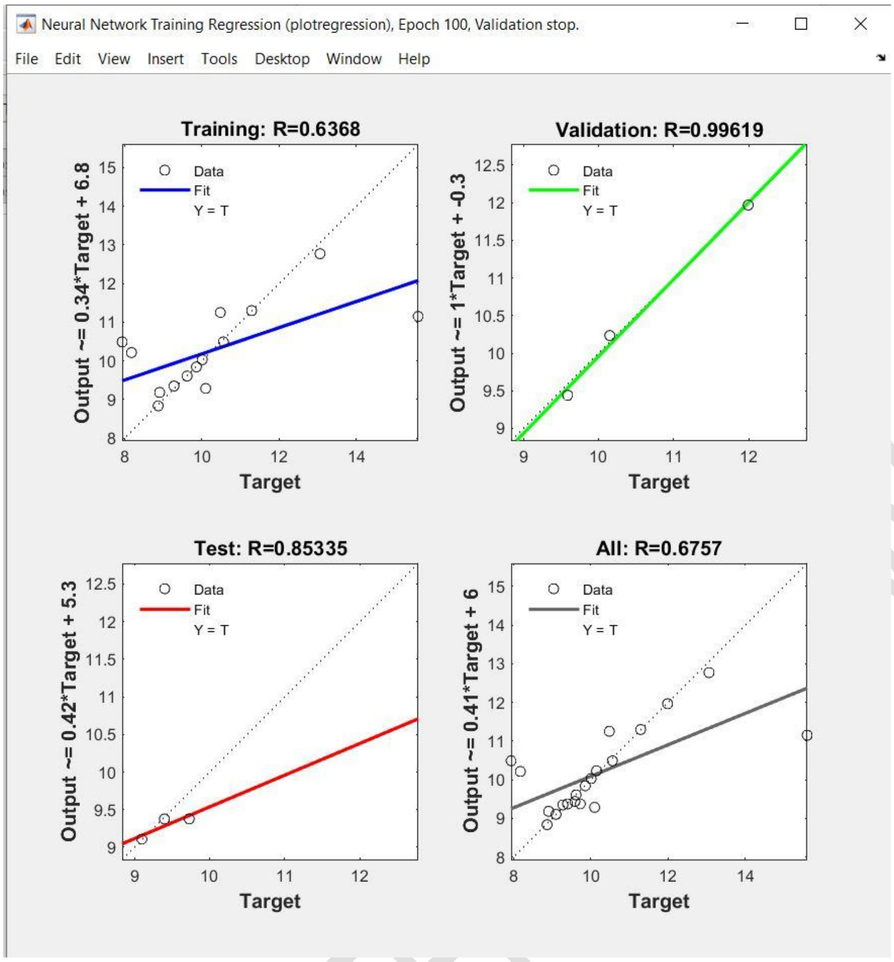

Fig. 3. Regression training output from LM Algorithm in ANN

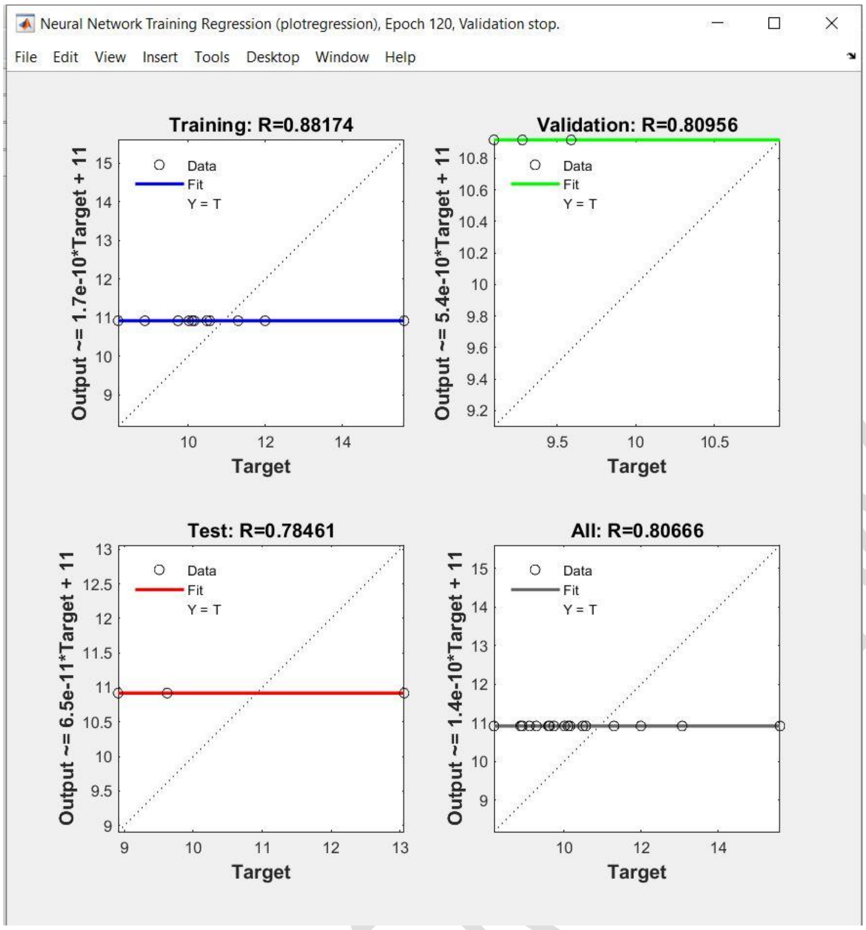

Fig. 4. Regression training output from LM Algorithm in ANN

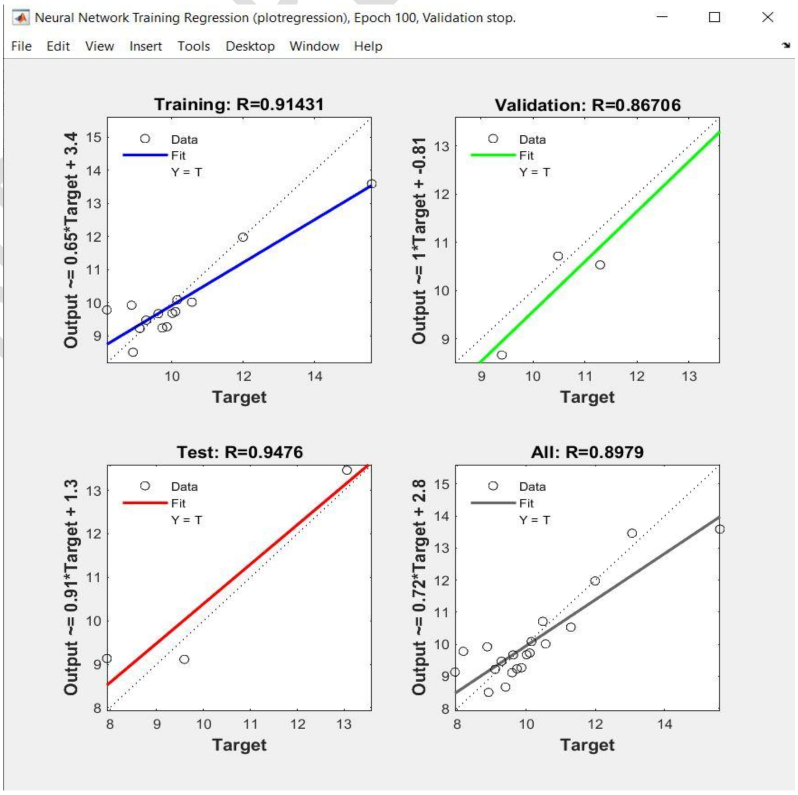

Fig. 5. Regression training output from LM Algorithm in ANN

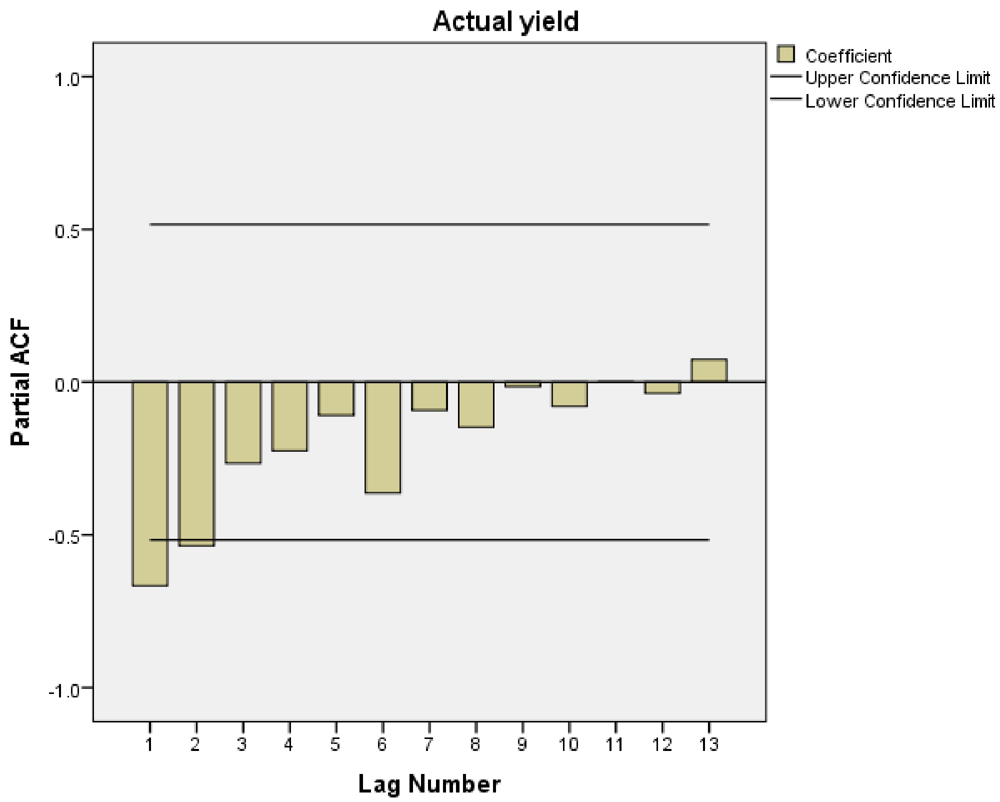

Fig 6. PACF graph from ARIMA model showing significant spikes for autoregressive (p) value

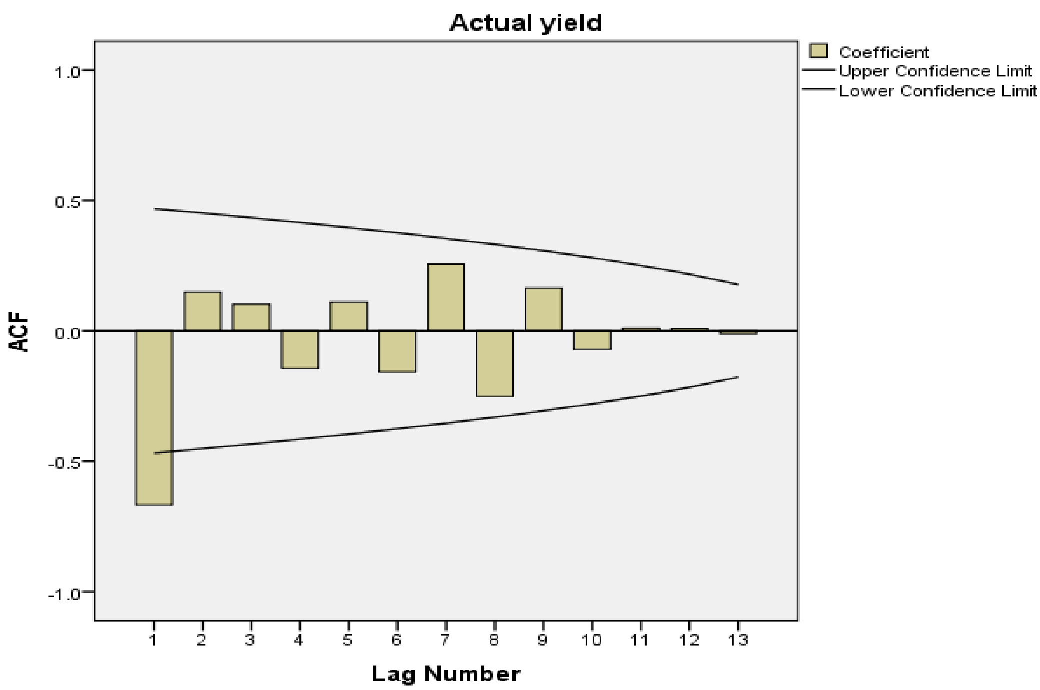

Fig 7. ACF graph from ARIMA model showing significant spikes for moving average (q) value

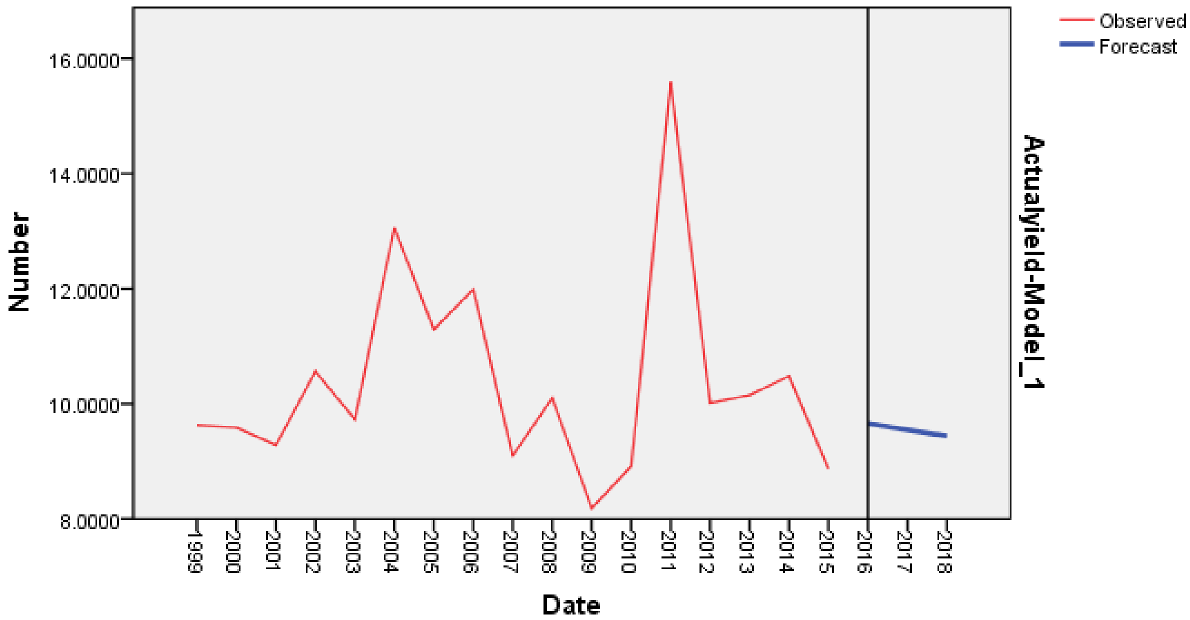

Fig 8. Observed and forecasted mustard yield using ARIMA model

		Correlation Matrix Udaipur (1999-2018)							
Generalised stages	**Metweek**	**Tmax**	**Tmin**	**RH1**	**RH2**	**WS**	**RF**	**SS**	**EVP**
Germination and Emergence	**40**	.023	.112	-.093	-.003	-.161	-.122	.023	.087
	41	-.089	.272	.044	.359	.060	**.711**	-.185	-.026
	42	-.186	.284	.138	**.433**	-.055	-.046	-.130	-.047
	43	-.180	-.100	.150	.118	-.152	.095	.056	-.105
Flowering	**44**	.056	-.001	.065	-.088	-.057	-.023	.230	.063
	45	.029	.041	.121	-.025	-.072	-.012	-.304	-.013
	46	-.132	-.032	.089	-.081	.147	-.029	.212	.107
	47	.017	.037	.129	-.041	.127	-.118	-.107	.012
	48	.130	.052	.107	.228	.027	0.00	.119	.005
	49	-.027	.057	.219	.392	.038	-.031	-.232	-.090
Pod formation and fruiting	**50**	-.009	.051	.300	.166	.013	.140	-.010	-.074
	51	-.068	-.018	.249	.085	-.045	.192	-.195	-.142
	52	.048	.009	.067	-.084	.053	-.135	.106	-.031
	1	-.108	.000	.373	.301	-.192	.365	-.107	-.204
	2	-.090	.002	.250	.288	.011	.164	-.239	-.132
	3	-.049	-.005	.062	.001	.009	-.178	.053	-.110
Ripening stage	**4**	-.230	-.031	.166	.046	.079	-.090	-.098	-.193
	5	-.282	-.024	.210	.110	-.045	-.016	-.298	-.309
	6	-.130	-.059	.068	.008	-.029	-.009	.043	-.120
Full Maturity	**7**	-.125	-.001	.272	.085	-.019	-.085	-.024	-.286
	8	.127	.049	.119	.016	-.097	-.082	.075	.055
	9	**-.503**	-.143	-.025	-.011	.202	.048	.090	-.033
	10	-.144	-.043	.099	-.013	.147	-.009	.087	-.195

	11	-.093	.124	.194	.008	.224	-.327	-.017	-.028
	12	-.134	-.137	.088	-.077	-.122	-.021	.183	-.129
	13	.113	-.040	.035	-.073	.154	-.123	.133	.003

Table 8. Correlation of weather variables with growth stages of wheat