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Forecasting wheat productivity in Punjab, India: A weather-based model approach using detrended data and regression analysis

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सार – भारत में, पंजाब के तीन जिलों में गेहूं की उत्पादकता का सटीक पूर्वानुमान लगाने के लिए मौसम आधारित मॉडल विकसित किए गए थे, जो फसल की कटाई से ढाई महीने पहले ही गेहूं की उपज का सटीक अनुमान लगाते थे। मौसम के मापदंडों में रुझान की पहचान मान-केंडल, सेन के ढलान और पेटिट के परीक्षण का उपयोग करके की गई थी। रैखिक और गैर-रैखिक मॉडलों में से, समय के साथ गेहूं की उत्पादकता पर तकनीकी कारकों के प्रभाव को समाप्त करने में लॉजिस्टिक मॉडल सबसे प्रभावी पाया गया। वनस्पति अवधि के दौरान चौदह सप्ताह के मौसम के आंकड़ों से प्राप्त डिट्रेंडेड डेटा का उपयोग करके गेहूं की उत्पादकता का पूर्वानुमान लगाया गया था। मौसम सूचकांकों पर डिट्रेंडेड गेहूं उत्पादकता के लिए चरणबद्ध प्रतिगमन तकनीक ने अमृतसर, लुधियाना और पटियाला जिलों के लिए मॉडल II को सर्वश्रेष्ठ बताया, मॉडल ने निष्कर्ष निकाला कि गेहूं की खेती के मौसम में अधिकतम गर्म और रात के ठंडे तापमान से विप्रवृत्त गेहूं की उत्पादकता में वृद्धि होगी, जबकि सुबह के समय वर्षा और सापेक्ष आर्द्रता में वृद्धि से विप्रवृत्त गेहूं की उत्पादकता में कमी आएगी और परिणामस्वरूप उत्पादन में भी कमी आएगी।

ABSTRACT. Weather-based models were developed to accurately forecast wheat productivity in three districts of Punjab, India, predicting the wheat yield with accuracy as early as two and a half months before the crop harvest. The trends in weather parameters were identified using Mann-Kendal, Sen's Slope and Pettitt's test. Amongst the linear and non-linear models, the logistic model was found to be the most effective in eliminating the influence of technological factors on wheat productivity over time. Forecasting of wheat productivity was done using detrended data derived from fourteen weeks of weather data during the vegetative period. The stepwise regression technique for detrended wheat productivity on weather indices revealed model II best for Amritsar, Ludhiana and Patiala districts, explaining 60%, 67% and 52% variation in the detrended wheat productivity and had root mean square percentage error 8.57%, 6.93% and 6.20% respectively. The model concluded that warm maximum and cool night temperatures of the wheat growing season will increase detrended wheat productivity, whereas an increase in rainfall and relative humidity in the morning will decrease detrended wheat productivity and hence the production.

Key words - Wheat, Yield forecasting, Linear, Non-linear, Weather, Indices.

1. Introduction

Wheat (*Triticum Aestivum)* is a major cereal crop during the *rabi* season. Punjab is a major wheat-growing state of India, which contributes 38% (2016-2017) of wheat to the central pool of the country from just 1.54% of the total geographical area of the country. Wheat productivity of Punjab increased from 2238 kg/ha (1970 - 1971) to 4563 kg/ha (2000 - 2001), almost doubling in thirty years, but further declined to 4304 kg/ha during 2014 - 2015 and then increased to 5077 kg/ha in 2017 - 2018 (Mahal and Kaur, 2018).

Productivity increased initially due to the introduction of high-yielding varieties in the late 1960s and higher use of inputs like fertilizers and other plant protection technologies. As the input use increases, there can be other factors for the decline in wheat productivity. A fluctuation in productivity in a short time can be due to the impact of weather parameters. Wheat productivity was greatly influenced by technological factors and weather parameters (Bal *et al*., 2004). The weather parameters are the uncontrollable source of variability in crop productivity. Weather variability is one of the main factors causing productivity to change year to year, as no two growing seasons experience the same weather (Lobell and Burke, 2010). For example, if temperatures are too high during the growing season, the wheat plants may experience heat stress, reducing growth and yield.

Similarly, if there is insufficient rainfall, the plants may suffer from drought stress, which can also reduce yield. Also, during different crop growth stages, the weather affects the crop differently. In the vegetative phase, the increase in the total rainfall more than the average has a harmful effect on the yield. The minimum temperature and relative humidity of rice yield during the reproductive and ripening phases vary from their averages and are susceptible to change (Huda *et al.*, 1975). Cooling of the growing season at night affects change in wheat production (Lobell *et al.*, 2005).

On the other hand, if there is too much rainfall, particularly at anthesis and grain filling stage of the growth cycle, it can cause waterlogging or other problems that can also reduce yield. Overall, the variability in weather can cause significant year-to-year fluctuations in wheat yield, making it challenging for farmers to plan and manage their production effectively. Thus, there was a need to analyze the effect of weather variables on crop productivity and to create a predictive model that can estimate future yields based on current or forecasted conditions.

Statistical modelling can forecast wheat yields by analyzing historical data on weather and previous yields. Various statistical models can be used for this purpose, including linear regression, time-series analysis and machine-learning algorithms. The results of these models can not only help farmers prepare for and mitigate the impact of weather-related risks but also enhance economic benefits and provide better environmental sustainability. Pre-harvest agricultural forecasts are essential for planting, formulating, and implementing policies relating to storage, marketing, prices and distribution and for import and export.

This paper attempted to develop pre-harvest crop-weather forecasting models for wheat crops of Punjab state in India using the modified Hendrick and Scholl technique (Kumar *et al.*, 2016) on detrended yield.

2. Materials and methods

The study was conducted for three districts of Punjab, *i.e.* Amritsar, Ludhiana and Patiala. Amritsar is located at 31.63º N latitude and 74.87º E longitude, Ludhiana at 30.9º N latitude and 75.85º E longitude and Patiala at 30.34º N latitude and 76.39º E longitude. The location map of selected wheat growing areas in Punjab is shown in Fig. 1.

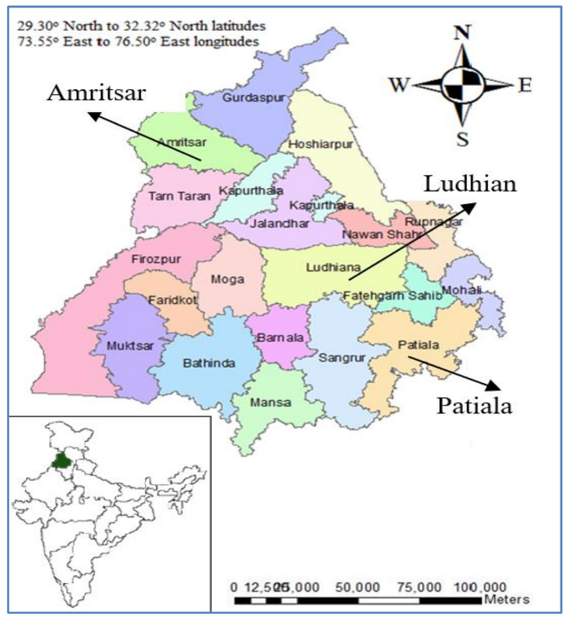

Fig. 1. Map of Punjab state.

2.1. *Data and crop description*

The wheat yield data of forty-eight years (1970-71 to 2017-18) for Amritsar, Ludhiana and Patiala districts had been collected from various statistical abstracts of Punjab (GoP 1971-2018). The daily weather data of forty-eight years (1970-71 to 2017-18) for variables maximum temperature (X_1) ºC, minimum temperature (X_2) ºC, rainfall (X_3) mm, relative humidity morning (X_4), relative humidity evening (X_5) % and bright sunshine hours (X_6) hrs had been collected from Department of Climate Change and Agricultural Meteorology, Punjab Agricultural University, Ludhiana. The daily data of weather variables were converted into weekly data by taking averages for all the variables except for rainfall; totals were calculated.

Wheat crop from sowing (October-November) to harvest (April) includes 26 standard meteorological weeks (SMW), *i.e.*, 44th SMW (29th Oct - 4th Nov) of the current year and 17th SMW (23rd April - 29th April) of the following year. The wheat growing period of 26 weeks was further divided into two periods: The vegetative period and the grain-filling period. The vegetative period of 14 weeks starts from 44th SMW (29th Oct - 4th Nov) to 5th SMW (29th Jan - 4th Feb) and the grain filling period of 12 weeks was from 6th SMW (5th Feb - 11th Feb) to 17th SMW (23rd April - 29th April). The present study was focused on forecasting before harvesting. So, the vegetative period of the wheat crop, constituting fourteen weeks for each weather variable was utilized for analysis. The data of six weather variables; maximum temperature, minimum temperature, rainfall, relative humidity morning, relative humidity evening and bright sunshine hours (X_1, X_2, X_3, X_4, X_5, X_6) were available for Ludhiana district and the data of three weather variables; maximum temperature, minimum temperature and rainfall (X_1, X_2, X_3) for Amritsar and Patiala districts.

2.2. *Trends in weather variables*

2.2.1. *Mann-Kendall test*

The trend in weather variables was examined by using the Mann-Kendall test. The Mann-Kendall (M.K.) test (Mann 1945 and Kendall 1975) is usually used to detect an upward or downward trend (*i.e.*, monotonic trends) in a series of hydro meteorological data (climate data) and environmental data. This test produces a Zs statistic score, which if > 0 suggests the presence of an increasing trend, < 0 suggests the presence of a decreasing trend and = 0 suggests no trend in the data at a specific significance level (α = 0.01 or α = 0.05). Here, Zs is computed as follows with the condition of sample size >10,

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{Var\,(S)}}, if\ S > 0 \\ 0, \qquad if\ S = 0 \\ \frac{S+1}{\sqrt{Var\,(S)}}, if\ S < 0 \end{cases}$$

Here, Var (S) is the variance of Mann Kendall test statistic (S) and computed as follows:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t+5)}{18}$$

Here, n is the number of data points, m is the number of tied groups and t_i denotes the number of ties of extent i. A tied group is a set of sample data having the same value.

As far as S statistic is concerned, it is

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sgn(x_j - x_i)$$

Where n is the number of data points, x_i and x_j are the data values in time series i and j (j>i), respectively and *sgn* $(x_j - x_i)$ is the sign function as:

$$sgn(x_j - x_i) = \{+1, if\,(x_j - x_i) > 0; 0, if\,(x_j - x_i) = 0; -1, if\ (x_j - x_i) < 0\}$$

2.2.2. *Sen's Slope*

Sen's Slope estimator (Sen, 1968) determines the actual slope (change per unit time) when a time series follows a linear trend. The slope estimates of N pairs of data are computed by:

$$Q_i = \frac{x_j - x_k}{j - k}\ for\ i = 1, \ldots.., N$$

Where x_j and x_k are data values at time j and k (j > k). The median of these N values of Q_i is a Sen's slope estimator.

2.2.3. *Pettitt test*

The Pettitt test identifies a point at which the values in the data change, which Pettitt developed. This test was used to determine the occurrence of a changing point in the weather parameters. The test statistic is given by:

$$U_{t,T} = \sum_{i=2}^{n}\sum_{j=1}^{i-1} sgn(X_i - X_j)$$

$$sgn\,(x_j - x_i) = \{+1, if\ (x_j - x_i) > 0; 0, if\,(x_j - x_i) = 0; -1, \quad \text{if } (x_j - x_i) < 0\,\}$$

The test statistic counts the number of times a member of the first sample exceeds a member of the second sample. The null hypothesis of Pettitt's test is the absence of a changing point. Its statistic k (t) and the associated probabilities used in significance testing are given (Pettitt, 1979): The non-parametric Mann-Kendall and Sen's methods were used to determine whether there was a positive or negative trend in weather data with their statistical significance. The occurrence of abrupt changes was detected using Pettit's test.

$$K_T = Max\left|U_{t,T}\right| 1 \leq t \leq T$$

$$P_{OA} = 2\,exp\left\{\frac{-6(K^+)^2}{(T^3 + T^2)}\right\} \quad for\ \ T \to \infty$$

TABLE 1

Linear and Non-Linear Models

Linear models		Non-linear models	
Simple Linear	$Y_t = \beta_0 + \beta_1 t + e_t$	Monomolecular	$Y_t = c - (c-b)exp(-rt)$
Quadratic	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + e_t$	Logistic	$Y_t = \frac{c}{1+b\ exp(-rt)}$
Cubic	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_2 t^2 + e_t$	Gompertz	$Y_t = c\ exp\ [b \exp(-rt)]$
Fourth degree polynomial	$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4 t^4 + e_t$		

2.3**.** *Techniques applied*

The crop yield is affected by both technological changes and weather variability. The linear and non-linear regression models (Table 1), simple linear, quadratic, cubic, fourth-degree polynomial, monomolecular, logistic and Gompertz (Prajneshu 2010) were developed to see the effect of technological factors; high-yielding varieties, fertilizers, insecticides and pesticides in wheat productivity. The models were fitted for forty-six years of data (1969-70 to 2014-15), and three years of data (2015-16 to 2017-18) were used for validation. Where Y_t is wheat yield, β_0, β_1, β_2, … are parameters to be estimated, random error $e_t \sim N(0, \sigma^2)$, *c* is the carrying size of the system, *b* values at the initial time and *r* is the growth rate. The parameter estimates of non-linear models were obtained by using the Levenberg-Marquardt iterative method (Prajneshu, 2010).

The linear and non-linear models were compared based on goodness of fit statistic (Shcherbakov *et al.*, 2013); coefficient of multiple determination (R^2), adjusted R^2, Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE). Assumptions of residuals were also worked out. The detrended wheat yield was obtained from the best-fitted linear/non-linear models, which were further used as the dependent variable for crop-weather models to study the impact of weather parameters on wheat productivity.

2.4. *Weather indices approach*

Pre-harvest weather forecasting models have been used for fourteen weeks of data of the vegetative period of wheat crop starting from 44[th] SMW to 5[th] SMW. The standardized weekly weather data was used for this study and standardization was done by taking the deviation of each variable from its respective mean and dividing the deviation by the standard deviation. The modified Hendrick and Scholl weather indices approach (Agrawal *et al.*, 2005, 2007; Kumar *et al.*, 2016) was used to study the effect of weather variables on productivity.

In this approach, two indices were used for each weather variable: un-weighted (Z_{i0}) and weighted (Z_{i1}) of the i_{th} variable. The un-weighted indices (Z_{i0}) were simple average over 14 weeks and weighted indices (Z_{i1}) take care of the distribution of weather variables with particular reference to their importance in different weeks and are calculated as a weighted average, where weights are correlation coefficient of the respective variables with detrended wheat productivity. On a similar line, indices were calculated with products of weather variables (taking two at a time) for combined effects (interaction) of both un-weighted ($Z_{ii'0}$) and weighted ($Z_{ii'1}$) indices. The expression for weighted and un-weighted weather indices (Agrawal *et al.*, 1980) was given as follows:

(*i*) Un-weighted weather indices

$$Z_{i0} = \frac{\sum_{w=1}^{m} X_{iw}}{m} \quad \text{and} \quad Z_{ii'0} = \frac{\sum_{w=1}^{m} X_{iw} X_{i'w}}{m}$$

Where X_{iw} & $X_{i'w}$ represents i[th] and i'[th] weather variable (i, i'=1, 2, …,6) in w[th] week (w = 1, 2, …,14)

(ii) Weighted weather indices

$$Z_{i1} = \frac{\sum_{w=1}^{m} r_{iw} X_{iw}}{\sum_{w=1}^{m} r_{iw}} \quad \text{and} \quad Z_{ii'1} = \frac{\sum_{w=1}^{m} r_{ii'w} X_{i'w} X_{i'w}}{\sum_{w=1}^{m} r_{ii'w}}$$

Where r_{iw} represents the correlation between the detrended productivity and i[th] weather variable (X_{iw}) in w[th] week, rii'w represents the correlation between the detrended yield and product of the i[th] weather variables (X_{iw}) & i' weather variable ($X_{i'w}$) in w[th] week.

The stepwise regression analysis (Draper & Smith, 2003) was applied to generated weather indices to select the most significant generated variables from Z_{ij} and Zii'j (i, i'=1, 2, …,6, j = 0,1). The advantage of the stepwise regression model is that it allows the use of a small subset of most minor correlated variables without losing a significant portion of the explanatory power of the data, which minimizes the effect of multi-collinearity on the regression model. Thus, the stepwise regression analysis

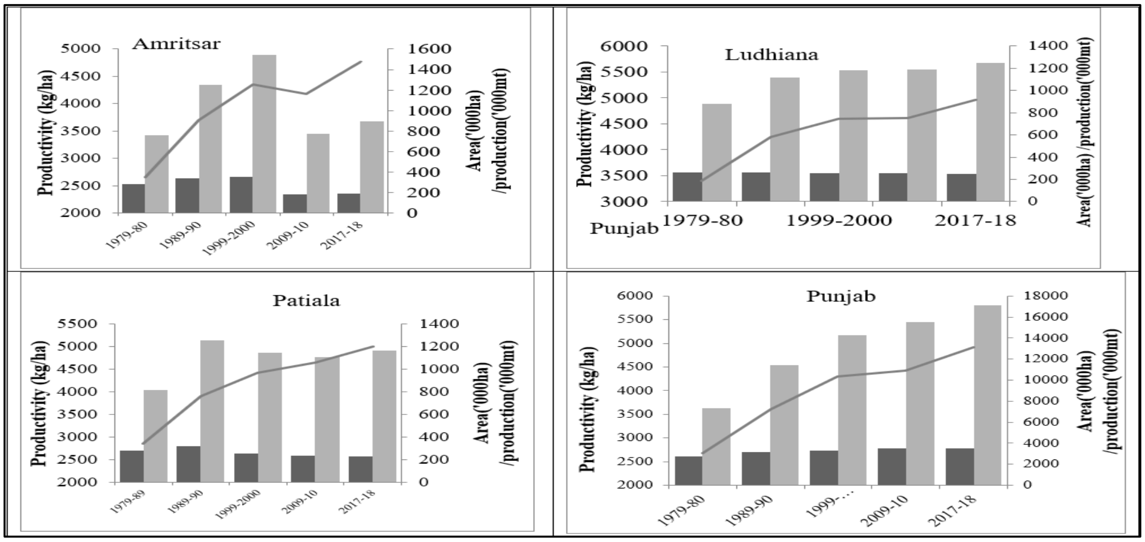

Fig. 2. Triennium ending area, production, and productivity.

technique using data of forty years (1970-71 to 2009-10) was applied to three models (with $p \leq 0.15$) as follows:

Model I (Unweighted model) :
$$Y = \beta_0 + \sum_{i=1}^{6} \beta_{i0} Z_{i0} + \sum_{i=1}^{6} \beta_{ii'0} Z_{ii'0} + e$$

Model II (Weighted model) :
$$Y = \beta_0 + \sum_{i=1}^{6} \beta_{i1} Z_{i1} + \sum_{i=1}^{6} \beta_{ii'1} Z_{ii'1} + e$$

Model III (Combined model) :
$$Y = \beta_0 + \sum_{i=1}^{6}\sum_{j=0}^{1} \beta_{ij} Z_{ij} + \sum_{i=1}^{6}\sum_{j=0}^{1} \beta_{ij} Z_{ii'j} + e$$

TABLE 2

Goodness of fit statistic

Coefficient of multiple determination	$R^2 = \frac{\sum_i(\hat{Y}_i-\bar{Y})^2}{\sum_i(Y_i-\bar{Y})^2} \quad 0 \leq R^2 \leq 1$
Adjusted R^2	$\bar{R}^2 = 1-(1-R^2)\frac{n-1}{n-p-1}$
Percentage forecast error	$PCFE = \left\lvert\frac{Y_i-\hat{Y}_i}{Y_i}\right\rvert \times 100$
Mean Absolute Percentage Error	$MAPE = \frac{1}{n}\sum\left\lvert\frac{Y_i-\hat{Y}_i}{Y_i}\right\rvert \times 100$
Root Mean Square Percentage Error	$RMSPE = \sqrt{\frac{1}{n}\sum\left(\left\lvert\frac{Y_i-\hat{Y}_i}{Y_i}\right\rvert \times 100\right)^2}$

* Where $\hat{Y}_i$ is the predicted value of the Y_i from the fitted model, $\bar{Y}$ is the overall mean, *n* is sample size, *p* is number of explanatory variables.

2.5. *Comparison and validation*

The data from forty-five years (1970-71 to 2014-15) was used for model development, and three years (2015-16 to 2017-18) for the validation of the model. The developed models were compared by using the goodness of fit statistic (Huang and Townshend, 2003), coefficient of determination (R^2), adjusted R^2, Percentage forecast error (PCFE), mean absolute percentage error (MAPE), and root mean square percentage error (RMSPE) as given in Table 2. A model with the highest value of R^2 adjusted R^2 and the lowest value of PCFE, MAPE and RMSPE was considered the best model.

2.6. *Analysis of residuals*

Analysis of residuals (Table 3) is required for testing assumptions of the regression model that the residuals are independent (run test), have zero means (student's t-test), constant variance (Spearman rank correlation), and normally distributed (Shapiro-Wilk test).

3. Results and discussion

Punjab, the granary of India, has been the second largest wheat-growing state after Uttar Pradesh. Thus, to see the growth in area, production and productivity, the triennium ending (T.E.) average was taken from 1970-71 to 2017-18. The pattern of area, production and productivity of Amritsar, Ludhiana, Patiala, and Punjab over time is shown in Fig. 2.

There was a 28 % increase in the area under wheat of Punjab during almost five decades (48 years). Wheat productivity increased throughout the period due to technological advancements but at a slow rate after T. E. 1999-2000. There was variability in inter-district wheat productivity. Production almost doubled up to T. E. 1999-2000, but after this period the increase was slow. It was due to a decline in the growth rate of productivity and area, leading to stagnation in production. This was a matter of concern, so there was a need to investigate the reasons for the decline in wheat productivity.

TABLE 3

Analysis of residuals

Testing	Test used	Null Hypothesis	Statistic
Randomness	Run test	Residuals are independent	$Z = \frac{\lvert r-\mu \rvert + h}{\sigma} \sim N\,(0,1) where\ h = \begin{cases} 0.5\ if\ r < \mu \\ -0.5\ if\ r > \mu \end{cases}$
Zero mean	Student's *t*-test	Residuals have zero mean	$t = \frac{\bar{x} - E(\bar{x})}{SE(\bar{x})} \sim t(n-1)$
Constant variance	Spearman rank correlation	Residuals have constant variance	$r'_{\lvert e \rvert, y} = 1 - \frac{6 \sum D_i^2}{n(n^2-1)}$ D_i : Difference between the ranks of absolute value of error and predicted value n : number of observations
Normality	Shapiro-Wilk	Residuals are normally distributed	$w = \frac{s^2}{b}$ $s^2 = \sum a(k)[x(n+1-k) - x(k)]\ where\ \ k = \begin{cases} 1,2, \ldots n/2\ when\ n\ is\ even \\ 1,2, \ldots (n-1)/2\ \ when\ n\ is\ odd \end{cases}$ $and\ b = \sum_{i=1}^{n} (x_i - \bar{x})^2$

TABLE 4

Result of Mann-Kendall and Sen's method

					Amritsar				
		T_{max}			**T_{min}**			**Rainfall**	
Month	P *	Tau**	Sen's slope	P *	Tau**	Sen's slope	P *	Tau**	Sen's slope
October	**0.0153**	**-0.2520**	**-0.0260**	**0.0264**	**0.2300**	**0.0496**	0.7108	-0.0415	0
November	0.5377	-0.0647	-0.0077	0.0766	0.1840	0.0328	0.3277	0.1080	0
December	0.0617	-0.1940	-0.0299	0.3136	0.1050	0.0107	0.6835	-0.0445	0
January	**0.3710**	**-0.4790**	**-0.0703**	0.8988	-0.0140	-0.0032	0.7099	0.0395	0.0615
February	0.5771	-0.0586	-0.0114	0.0564	0.1980	0.0324	0.5312	0.0658	0.1842
March	0.3328	0.1010	0.0226	0.4056	0.0869	0.0123	0.5248	-0.0667	-0.2189
April	0.8143	0.0253	0.0044	0.6527	0.0475	0.0062	0.5972	0.0557	0.0558
					Patiala				
Month	P *	Tau**	Sen's slope	P *	Tau**	Sen's slope	P *	Tau**	Sen's slope
October	0.4691	0.0759	0.0052	0.1064	0.1680	0.0183	0.2386	0.1280	0
November	**0.0019**	**0.3200**	0.0313	0.0688	0.1890	0.0235	0.8442	0.0228	0
December	0.7542	-0.0334	-0.0052	0.1065	0.1680	0.0233	0.9842	0.0031	0
January	**0.0037**	**-0.3010**	**-0.0426**	0.8910	0.0152	0.0025	0.8448	0.0213	0.0338
February	**0.0481**	**0.2050**	**0.0362**	**0.0291**	0.2260	0.0367	0.7765	0.0304	0.0385
March	**0.0438**	**0.2090**	**0.0453**	0.0688	0.1890	0.0239	0.4386	0.0817	0.1441
April	0.2863	0.1110	0.0250	0.4691	0.0758	0.0130	0.1729	0.1430	0.0911
					Ludhiana				
Month	P *	Tau**	Sen's slope	P *	Tau**	Sen's slope	P *	Tau**	
October	0.3886	-0.0870	-0.0075	**0.7150**	**0.4490**	**0.0741**	0.4501	0.0816	0
November	0.2033	0.1280	0.0111	**0.0006**	**0.3420**	**0.0499**	0.2941	-0.1120	0
December	0.6000	-0.0532	-0.0078	**0.0005**	**0.3490**	**0.0483**	0.8433	0.0211	0
January	**0.0045**	**-0.5281**	**-0.0359**	**0.0017**	**0.3140**	**0.0420**	0.5693	0.0578	0.1028
February	0.1019	0.1640	0.0221	**0.1070**	**0.4890**	**0.0678**	0.7828	-0.0285	-0.0570
March	**0.0102**	**0.2570**	**0.0490**	**0.1190**	**0.5340**	**0.0730**	0.9929	0.0017	0
April	0.3238	0.0993	0.0215	**0.3310**	**0.4150**	**0.0614**	0.5454	0.0614	0.0834

*P value < 0.05 tells that there is (monotonic) trend and P value >0.05, tells no monotonic trend, ** if τ is +ve, increasing trend and if τ is -ve, decreasing trend. The figures in bold values indicate significant values.

TABLE 5

Pettitt test

Month	T_{max}		T_{min}		Rainfall	
Amritsar						
	P-value	Change-point	P-value	Change-point	P-value	Change-point
October	**0.0460**	**1980-1981**	**0.0196**	1997-1998	0.6510	1986-1987
November	0.4516	1976-1977	0.1047	1997-1998	0.4879	1976-1977
December	0.1300	2001-2002	0.7668	2008-2009	0.7429	1990-1991
January	**0.3209**	**1996-1997**	1	1980-1981	1	1981-1982
February	0.9435	2008-2009	0.2658	2003-2004	1	1975-1976
March	0.4341	1996-1997	0.0745	1998-1999	0.4516	1995-1996
April	0.3845	1975-1976	0.2720	1997-1998	0.7077	2005-2006
Patiala						
Month	T_{max}		T_{min}		Rainfall	
	P-value	Change-point	P-value	Change-point	P-value	Change-point
October	0.1047	1997-1998	0.1521	1993-1994	0.6962	1994-1995
November	**0.0008**	**1996-1997**	0.2720	1975-1976	0.7911	1975-1976
December	1	2008-2009	0.2720	1983-1984	0.4006	1990-1991
January	0.0745	1996-1997	0.9831	1994-1995	0.7911	1981-1982
February	0.1370	1990-1991	0.1106	1984-1985	1	2010-2011
March	**0.0381**	**1996-1997**	0.0588	1999-2000	0.5558	1975-1976
April	0.1106	1996-1997	0.3247	1999-2000	0.4341	1979-1980
Ludhiana						
Month	T_{max}		T_{min}		Rainfall	
	P-value	Change-point	P-value	Change-point	P-value	Change-point
October	0.4789	1978-1979	0.0001	1993-1994	1	1994-1995
November	0.1563	1991-1992	**0.0071**	**1986-1987**	0.4624	1996-1997
December	1	1970-1971	**0.0045**	**1983-1984**	0.7702	1990-1991
January	**0.0081**	**1996-1997**	**0.0275**	**1984-1985**	0.7812	1989-1990
February	0.3308	1996-1997	**0.0001**	**1997-1998**	1	1996-1997
March	**0.0049**	**1996-1997**	**0.4240**	**1998-1999**	0.9185	1975-1976
April	**0.0479**	**1995-1996**	**0.0001**	**1995-1996**	0.9304	1974-1975

3.1. *Trend Analysis of Weather Variables*

According to results (Table 4) by Sen's slope estimator and Mann-Kendall, different districts showed varied trend in T_{max} and T_{min}. In addition, no significant change in rainfall was observed in all the districts. Amritsar district showed a significant decreasing trend in T_{max} in January (0.07 °C/year) and October (0.02 °C/year) and an increasing trend in T_{min} in October (0.05 °C/year). In Patiala, there is an increasing trend in T_{max} in all the months except December, January and April. Interestingly, a significant increase in minimum temperature was observed in all the months (0.042 - 0.073 °C /year) in the Ludhiana district, whereas a significant decrease in T_{max} in January (0.036 °C/year) and an increase in March (0.042 °C/year) was observed.

Based on the results of the Pettitt test, no significant change points were detected in the time series precipitation data of the selected districts. Significant change points were detected in the minimum monthly temperature series of the Ludhiana district (Table 5) and in October for the Patiala district. A significant change in

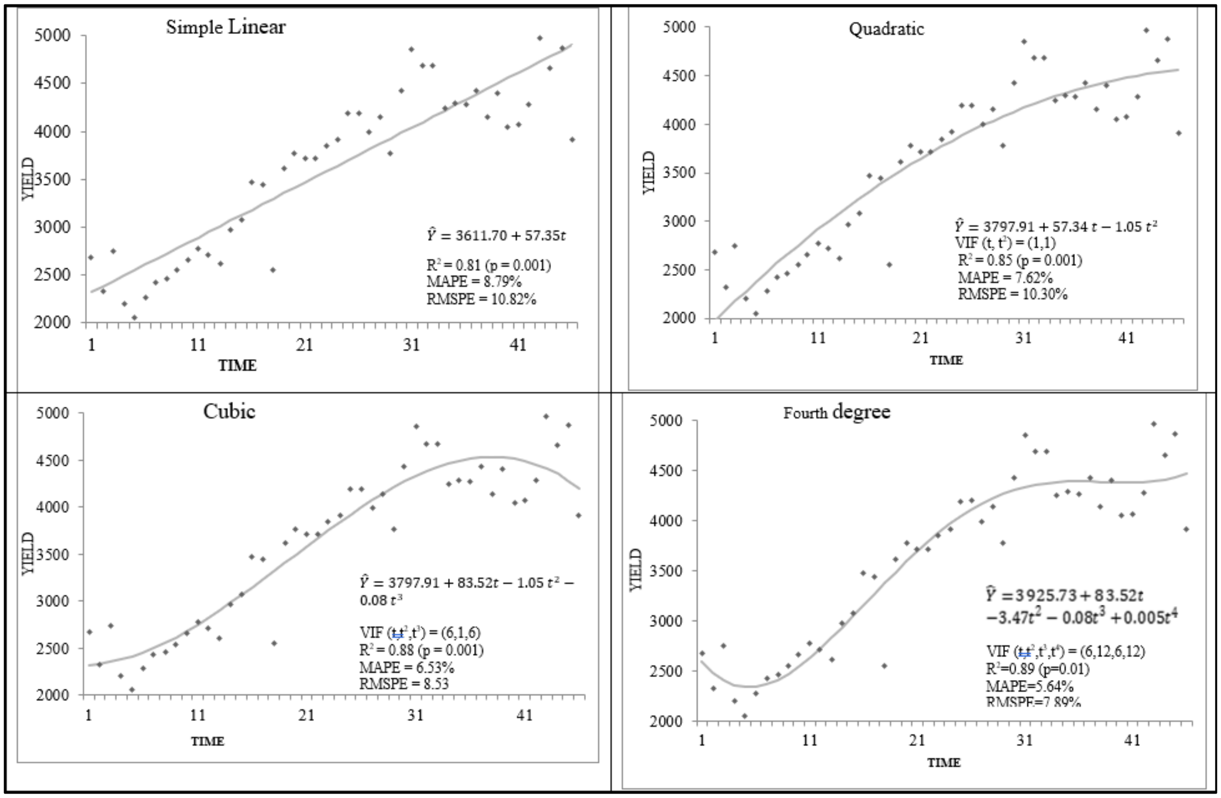

Fig. 3. Linear models of Amritsar district.

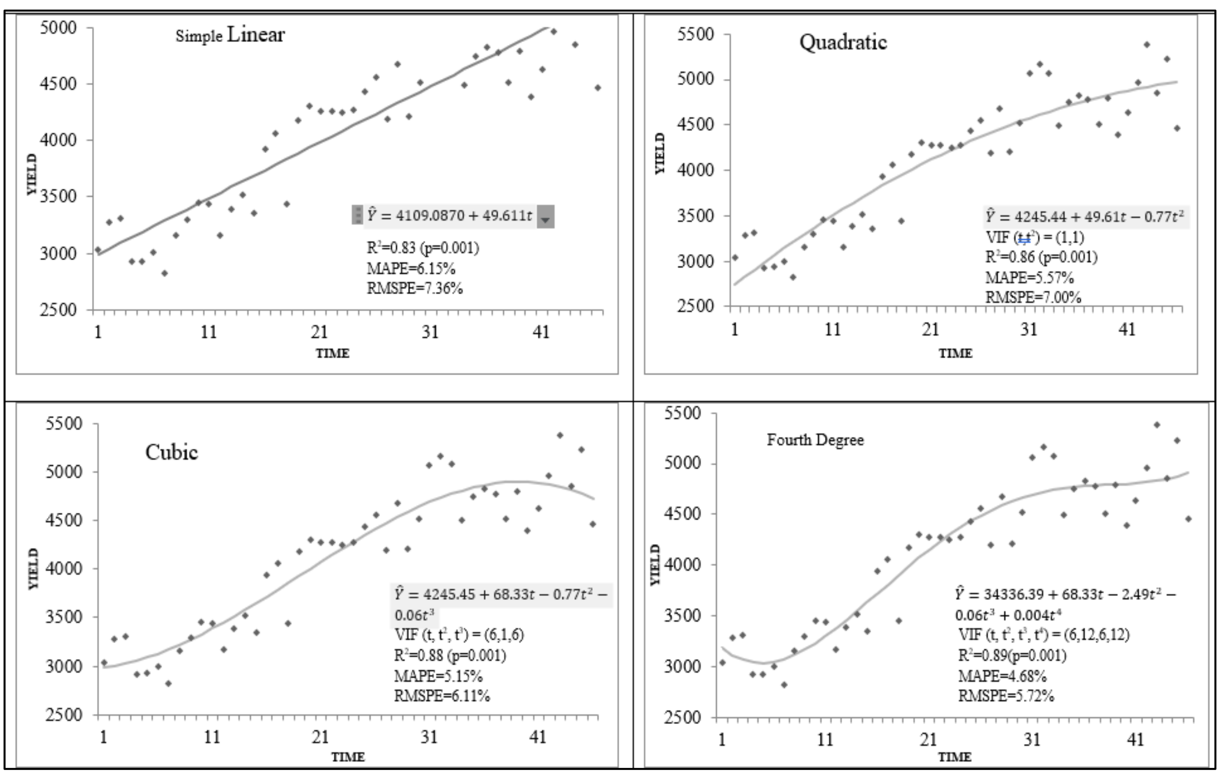

Fig. 4. Linear Models of Ludhiana district.

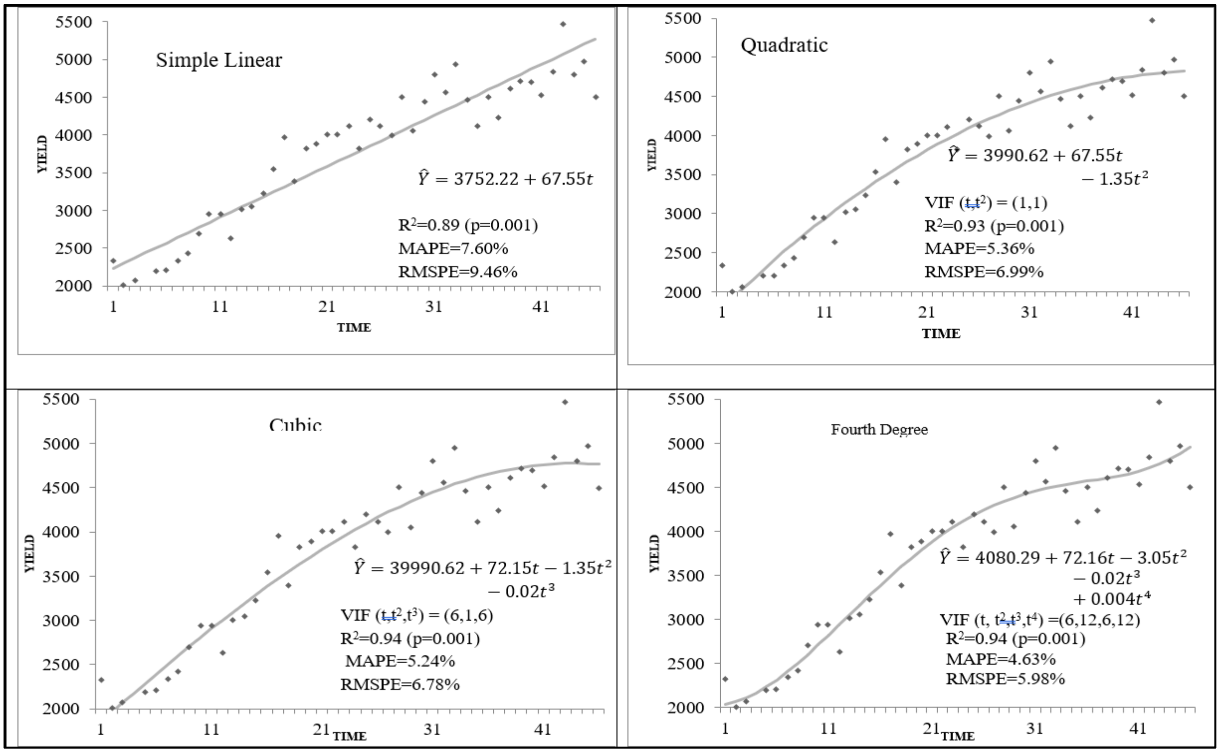

Fig. 5. Linear models of Patiala district.

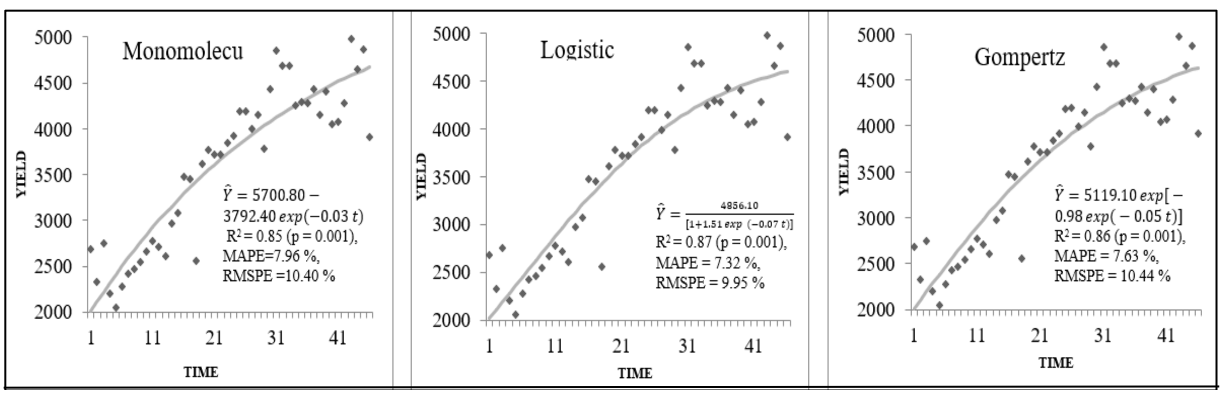

Fig. 6 Non-Linear models of Amritsar district.

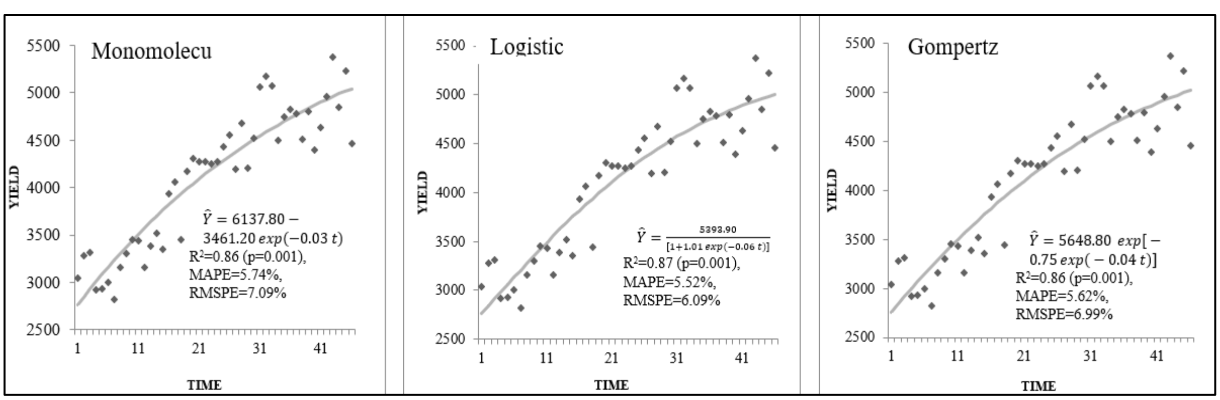

Fig. 7. Non-Linear models of Ludhiana district.

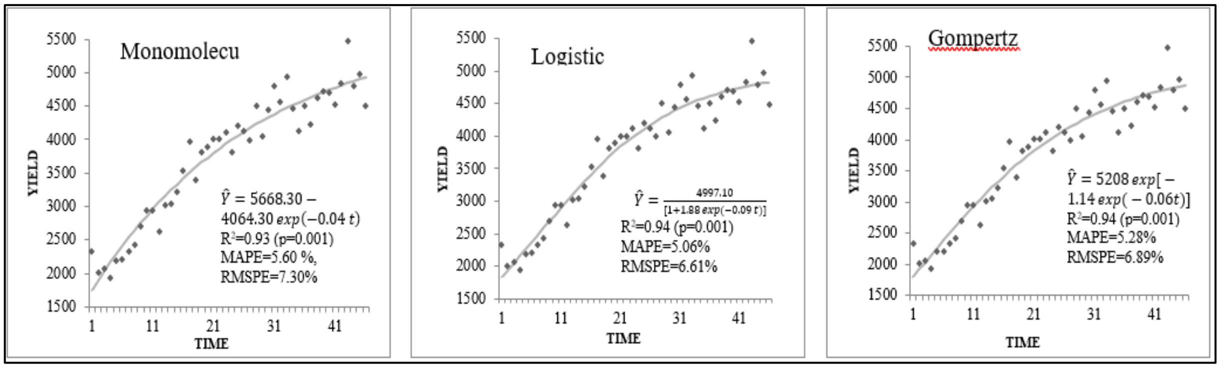

Fig. 8. Non-Linear models of Patiala district.

T_{max} values occurred in October (1980-81) and January month (1996-97) in Amritsar; January (1996-97), March (1996-97) and April (1995-96) in Ludhiana; and November (1996-97) and March (1996-97) in Patiala.

3.2. *Detrend wheat yield*

The linear and non-linear models (Panwar *et al.*, 2014) were used to see the effect of technological trends, high-yielding varieties, fertilizers, insecticides, pesticides, *etc*, in wheat productivity by taking time as the independent variable for Amritsar, Ludhiana and Patiala districts. The results of fitted linear models, as shown in Figs. 3 to 5, revealed that the fourth-degree polynomial model had been the best-fitted model based on the highest R^2, adjusted R^2 and lowest value of MAPE and RMSPE. However, due to the presence of multi-collinearity incubic and fourth-degree polynomial, the quadratic model was best fitted for Amritsar, Ludhiana, and Patiala districts, explaining 85%, 86% and 93% variations in wheat productivity and had RMSPE 10.30%, 7% and 6.99% respectively. Similarly, from non-linear models, as shown in Figs. 6 to 8, the logistic model was declared as best for Amritsar, Ludhiana and Patiala districts, explaining 87%, 87% and 94% variations in wheat productivity and had RMSPE 9.95%, 6.09% and 6.61% respectively. By comparing the linear and non-linear models (Table 6), it may be concluded that the logistic model was best fitted for the wheat productivity based on highest value of R^2 (0.87, 0.87, 0.94) and minimum value of MAPE (7.32%, 5.52%, 5.06%) and RMSE (9.95%, 6.09%, 6.61%) respectively for Amritsar, Ludhiana and Patiala district.

The validation of the best-fitted logistic model had been worked out from three years of data (2015-16 to 2017-18) and shown in Table 7. The percentage forecast error (PCFE) had been observed to be less than 8%, MAPE less than 7% and RMSPE less than 7%. The results of assumptions of residuals (Table 8) revealed that the logistic model followed all the assumptions of residuals: independence, zero mean, constant variance and normality for Amritsar, Ludhiana and Patiala districts at a 5% significance level.

Thus, the results of Amritsar, Ludhiana and Patiala districts showed that the logistic model was the best-fitted model for capturing technological trends in wheat productivity based on goodness of fit statistic; coefficient of determination more significant than 85%, PCFE less than 8%, MAPE less than 7% and RMSPE less than 7%. Similar results have been reported by Panwar *et al*. (2014), Mahal and Kaur (2018).

3.3. *Weather-based forecasting models*

The pre-harvest weather-based forecast models were developed by using detrended data of wheat productivity from the fitted logistic model and weather indices of the vegetative period of the wheat crop. The results of the Amritsar district, as shown in Table 9, revealed that based on the goodness of fit statistic, Model II (weighted model) was best fitted, explaining 60% variation in detrended productivity and had a minimum value of mean absolute percentage error (5.08%). The analysis of variance and parameter estimates of model II are shown in Table 10. The indices Z_{11} (weighted average maximum temperature) showed a significant positive effect on detrended wheat productivity, whereas Z_{31} (weighted average rainfall) and Z_{121} (weighted average interaction between maximum and minimum temperature) showed a significant adverse effect on detrended wheat productivity.

The plot of actual and predicted yield (Fig. 9) depicts slight variations in residuals except for 2014-15 due to a fall in yield. The plot showed that the percentage forecast error was less than 5% except for 2014-15, where MAPE was 5.08% and RMSPE was less than 9%.

The results of stepwise regression analysis for the Ludhiana district (Table 11) revealed that based on the goodness of fit statistic, model II was declared best-fitted model explaining 67% variation in detrended wheat

TABLE 6.

Best fitted Linear and Non-Linear Model for Amritsar, Ludhiana and Patiala

District	Models	Equation	R^2 (p-value)	MAPE	RMSPE
Amritsar	**Quadratic**	$\hat{Y} = 3797.91 + 57.34\,t - 1.05\,t^2$	0.85 (0.001)	7.62	10.30
	Logistic	$\hat{Y} = \frac{4856.10}{[1+1.51\,exp(-0.07t)]}$	0.87 (0.001)	7.32	9.95
Ludhiana	**Quadratic**	$\hat{Y} = 4245.44 + 49.61t - 0.77t^2$	0.86 (0.001)	5.57	7.00
	Logistic	$\hat{Y} = \frac{5393.90}{[1+1.01\,exp(-0.06\,t)]}$	0.87 (0.001)	5.52	6.09
Patiala	**Quadratic**	$\hat{Y} = 3990.62 + 67.55\,t - 1.35\,t^2$	0.93 (0.001)	5.36	6.99
	Logistic	$\hat{Y} = \frac{4997.10}{[1+1.88\,exp(-0.09t)]}$	0.94 (0.001)	5.06	6.61

TABLE 7.

Validation of logistic model for Amritsar, Ludhiana and Patiala

District	Actual Yield	Predicted Yield	PCFE	MAPE	RMSPE
	4478	4617.33	3.11		
Amritsar	4948	4633.12	6.36	4.65	4.84
	4866	4647.92	4.48		
	4670	5022.93	7.56		
Ludhiana	5093	5041.67	1.01	3.24	4.50
	5144	5059.53	1.64		
	4585	4844.24	5.65		
Patiala	5165	4856.61	5.97	6.67	6.49
	5272	4868.01	7.66		

TABLE 8.

Test of residuals for logistic model of Amritsar, Ludhiana and Patiala district

Testing		*Statistic (p-value)*	
	Amritsar	**Ludhiana**	**Patiala**
Randomness	-3.44^s (0.106)	-1.63^s (0.103)	-1.04^s (0.297)
Zero mean	0.04^s (0.966)	0.02^s (0.987)	0.02^s (0.982)
Constant variance	0.02^s (0.885)	0.04^s (0.776)	0.06^s (0.714)
Normality	0.98^s (0.756)	0.99^s (0.793)	0.97^s (0.246)

* **s**: H_0 accepted (assumption **s**atisfied) for α=0.05

TABLE 9.

Fitted models for Amritsar district

Models	Equation	R^2	Adj R^2	MAPE	RMSPE
Model I	$\hat{Y} = -0.03 + 1.11Z_{10}$	0.23	0.21	6.27	7.28
Model II/ Model III	$\hat{Y} = -0.03 + 0.54Z_{11} - 0.23Z_{31} - 0.04Z_{121}$	0.60	0.57	5.08	8.57

TABLE 10.

ANOVA and Parameter Estimates of model II for Amritsar district

		Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	R^2
Model	3	21.71	7.24	17.94	0.0001	0.60
Error	36	14.53	0.40			
Corrected Total	39	36.24				
			Parameter Estimates			
Variable	DF	Parameter Estimate	Standard Error	t value	Pr > |t|	Variance Inflation
Intercept	1	-0.03	0.11	-0.28	0.778	
Z_{11}	1	0.54	0.19	2.8	0.008	1.77
Z_{31}	1	-0.23	0.09	-2.47	0.018	1.54
Z_{121}	1	-0.04	0.02	-2.04	0.048	1.26

TABLE 11

Fitted Models of Ludhiana district

Models	Equation	R^2	Adj R^2	MAPE	RMSPE
Model I	$\hat{Y} = 0.09 + 0.89Z_{10} - 1.09Z_{30} - 1.42Z_{140} + 1.41Z_{460}$	0.40	0.34	6.24	7.28
Model II/ Model III	$\hat{Y} = -0.01 - 0.10\ Z_{21} - 0.09\ Z_{41} - 0.17\ Z_{121} + 0.09\ Z_{261}$	0.67	0.64	5.23	6.93

TABLE 12

ANOVA and Parameter Estimates of model II for Ludhiana district

		Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	R^2
Model	4	26.25	6.56	18.01	0.0001	0.67
Error	35	12.75	0.36			
Corrected Total	39	39.00				
		Parameter Estimates				
Variable	DF	Parameter Estimate	Standard Error	t value	Pr > |t|	Variance Inflation
Intercept	1	-0.01	0.11	-0.03	0.977	
Z_{21}	1	-0.10	0.04	-2.86	0.007	1.20
Z_{41}	1	-0.09	0.04	-2.24	0.031	1.29
Z_{121}	1	-0.17	0.06	-2.83	0.007	1.29
Z_{261}	1	0.09	0.03	2.55	0.015	1.68

TABLE 13

Fitted Models for Patiala district

Models	Equation	R^2	Adj R^2	MAPE	RMSPE
Model I	$\hat{Y} = 0.01 + 0.59\ Z_{10}$	0.07	0.04	5.05	6.12
Model II	$\hat{Y} = -0.10 - 0.07Z_{21} - 0.13\ Z_{31} + 0.33\ Z_{121}$	0.52	0.47	4.50	6.20
Model III	$\hat{Y} = -0.17 - 0.51\ Z_{130} - 0.08\ Z_{21} - 0.17\ Z_{31} + 0.31\ Z_{121}$	0.55	0.50	4.78	6.42

productivity. The analysis of variance and parameter estimates of model II are given in Table 12.

The significant indices Z21 (weighted average minimum temperature), Z41 (weighted average relative humidity morning) and Z121 (weighted average interaction between maximum temperature and rainfall) showed a negative effect on detrended wheat productivity whereas Z261 (weighted average interaction between minimum temperature and bright sunshine) had positive effect on detrended productivity. The plot of actual and predicted productivity (Fig. 10) depicted more variations in the residuals of 2011-12, 2014-15 and 2017-18 due to unexpected variability in productivity. The wheat productivity was maximum in 2011-12 (5375 kg/ha) due to favorable conditions, but it declined to a minimum in the year 2014-15 (4462 kg/ha), causing maximum PCFE (14.09%) and then regaining to 5144 kg/ha in 2017-18.

The results of stepwise regression for the Patiala district were quite different from those of the Amritsar & Ludhiana districts & shown in Table 13, model III seems to be best-fitted based on highest value of R^2(0.55) & adjusted R^2(0.50) but MAPE & RMSPE value were also higher (4.78%, 6.42%) than that of model II (4.50%, 6.20%).

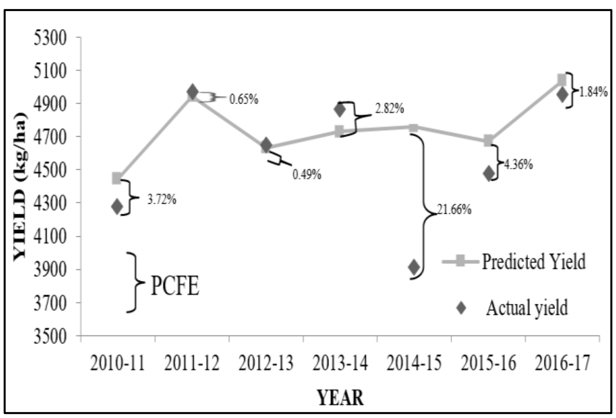

Fig. 9. Percentage forecast error of model II for Amritsar district.

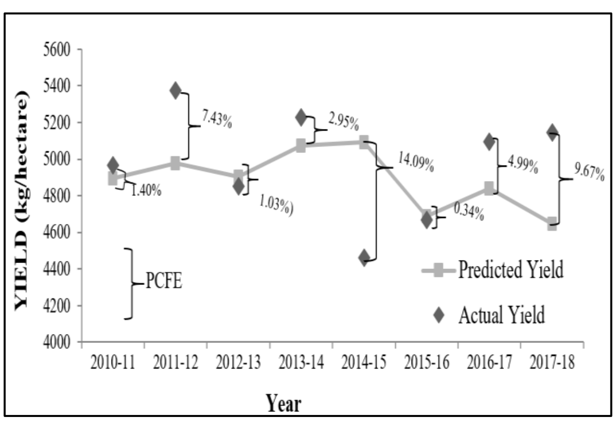

Fig. 10. Percentage forecast error of model II for Ludhiana district.

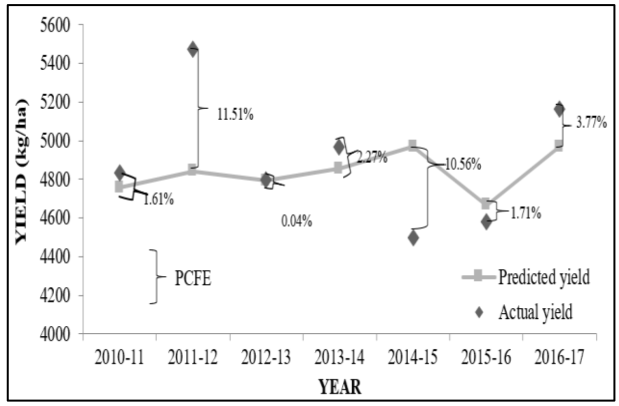

Fig. 11. Percentage forecast error of model II for Patiala district.

Therefore, based on the lower value of MSPE and RMSPE, model II was chosen as the best-fitted for forecasting the wheat productivity of the Patiala district. Model II explained a 52% variation in detrended wheat productivity. Analysis of variance and parameter estimates of model II (Table 14) revealed that indices Z_{21} (weighted average minimum temperature) and Z_{31} (weighted average rainfall) had a significant adverse effect on the detrended wheat productivity, whereas Z_{121} (weighted average interaction between maximum and minimum temperature) had a significant positive effect on detrended wheat productivity.

The model validation was worked out and shown in Fig. 11, revealing that the percentage forecast error was less than 4% (excluding 2011-12 and 2014-15), MAPE 4.5% and RMSPE 6.20%. The large variation in residuals was depicted during 2011-12 and 2014-15 due to unexpected variability in productivity.

As model II was the best-fitted model for the Amritsar, Ludhiana and Patiala districts, the assumptions of residuals, randomness, zero mean, constant variance and normality, as given in Table 15, were worked out to check the model suitability. The results showed that at a 5% significance level, the selected models followed all the assumptions of residuals.

Thus, the results of all the districts showed that the weighted weather indices could clearly depict the influence on wheat yield than unweighted ones. The weighted model (Model II) came best in all three districts: Amritsar, Ludhiana and Patiala, as shown in Table 16.

It was observed from the models that Z_{11} (weighted maximum temperature) had a positive effect on the productivity of the Amritsar district and Z_{21} (weighted minimum temperature) had a negative effect on the

TABLE 14.

ANOVA and Parameter Estimates of model II for Patiala district

		Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	R^2
Model	**3**	20.12	6.71	12.79	0.001	0.52
Error	**36**	18.88	0.52			
Corrected Total	**39**	39.00				
		Parameter Estimates				
Variable	DF	Parameter Estimate	Standard Error	t value	Pr > |t|	Variance Inflation
Intercept	**1**	-0.10	0.12	-0.80	0.430	
Z21	**1**	-0.07	0.03	-2.51	0.020	1.06
Z31	**1**	-0.13	0.04	-2.89	0.010	1.19
Z121	**1**	0.33	0.12	2.68	0.010	1.18

TABLE 15.

Test of residuals of model II for Amritsar, Ludhiana, and Patiala districts

Testing	Statistic (p-value)		
	Amritsar	Ludhiana	Patiala
Randomness	-1.26^s (0.216)	-0.79^s (0.430)	-0.14^s (0.885)
Zero mean	0^s (1)	0^s (1)	0^s (1)
Constant variance	0.08^s (0.615)	-0.17^s (0.300)	-0.04^s (0.809)
Normality	0.99^s (0.869)	0.98^s (0.628)	0.95^s (0.078)

* **s**: H_0 accepted (assumption **s**atisfied) for α=0.05

TABLE 16.

Best pre-harvest forecast model

District	Forecast Model II	R^2	MAPE	RMSPE
Amritsar	$\hat{Y} = -0.03 + 0.54Z_{11} - 0.23Z_{31} - 0.04\,Z_{121}$	0.60	5.08	8.57
Ludhiana	$\hat{Y} = -0.01 - 0.10\,Z_{21} - 0.09\,Z_{41} - 0.17\,Z_{121} + 0.09\,Z_{261}$	0.67	5.23	6.93
Patiala	$\hat{Y} = -0.10 - 0.07\,Z_{21} - 0.13\,Z_{31} + 0.33\,Z_{121}$	0.52	4.50	6.20

productivity of the Ludhiana and Patiala districts. The indices Z_{121} showed a negative effect on the detrended wheat productivity of the Amritsar and Ludhiana districts, implying that warm maximum and cool night temperatures of the growing season of wheat will increase wheat productivity. In contrast, it showed a positive effect on the detrended wheat productivity for the Patiala district, implying that increase in maximum and minimum temperature increases the wheat productivity. The similar effects of maximum and minimum temperature on wheat productivity for different regions were depicted by Lobell *et al*. (2005), Kumar *et al*. (2014) and Gupta *et al*. (2018). The indices Z_{31} (weighted average rainfall) had a negative effect on the detrended productivity of the Amritsar and Patiala districts, showing that an increase in rainfall more than the average had a harmful effect on detrended productivity. The indices Z_{41} (weighted average relative humidity morning) had a negative impact on the productivity of the Ludhiana district.

4. Conclusions

Punjab has made rapid strides in agriculture after independence. However, the productivity in the state is highly influenced by the prevailing weather conditions. The present study was conducted to understand the growth in area, production, and productivity of wheat for Punjab state and to develop a yield forecasting tool. The results revealed that for 48 years (1970-71 to 2017-18), there was no trend in annual/monthly rainfall. However, there had been a significant increase in annual and monthly maximum and minimum temperatures except for January, which witnessed a decreasing trend in all three selected districts (Amritsar, Ludhiana and Patiala) of the state. Wheat productivity increased throughout the period but slowly after T. E. 1999-20. Production almost doubled up to T. E. 1999-20 but after that increased at a slow rate. It was due to a decline in the growth rate of productivity and area, leading to stagnation in production. Pre-harvest forecast models were developed to see the effect of weather parameters on wheat productivity in Punjab, Amritsar, Ludhiana and Patiala.

The time trend was excluded by using Linear and Non-Linear models: simple linear, quadratic, cubic, fourth-degree polynomial, monomolecular, logistic and Gompertz. The logistic model came with the best fit based on the goodness of fit statistic. The detrended wheat productivity was well forecasted using logistic model. The weighted and un-weighted weather indices were developed using standardized 14 weeks of data of the vegetative period of wheat crop starting from 44th SMW to 5th SMW. Three models were developed Model I (Un-weighted), Model II (Weighted) and Model III (combined). The weighted model (Model II) was suitable for forecasting detrended wheat productivity for Amritsar, Ludhiana and Patiala districts and followed all the assumptions of residuals. The Model II explained 60%, 67% and 52% variations in detrended wheat productivity for Amritsar, Ludhiana and Patiala districts and had MAPE less than 6% and RMSPE less than 9%. It had been concluded from the models that the warm maximum and cool night temperature of the growing wheat season will increase the detrended wheat productivity.

In contrast, increasing rainfall and relative humidity in the morning will decrease the detrended wheat productivity and, hence, the production. A well-organized forecasting model before harvesting is helpful in policymaking related to prices, marketing, and storage and especially for implementing agricultural development at the state and country levels. Crop yield forecasting using statistical models in Punjab can significantly benefit farmers, policymakers and other stakeholders, contributing to food security, economic growth, and environmental sustainability.

Disclaimer: The contents and views presented in this research article/paper are the views of the authors and do not necessarily reflect the views of the organizations they belongs to.

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Data availability

The data will be made available on request.

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