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Mustard Yield Prediction using State Space Models

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Authors' contributions

This work was carried out in collaboration between both authors. Author EH designed the study, performed the statistical analysis. Author BKH wrote the protocol and wrote the first draft of the manuscript. Authors EH and BKH managed the analyses of the study. Both authors managed the literature searches. Both authors read and approved the final manuscript

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ABSTRACT

Forecasting of agricultural outputs well in advance has always been the focus of numerous researchers due to its direct implications on various areas of the society. This study aims to develop State Space Models (SSMs) with weather as an exogenous input over the commonly used ARIMA and regression analysis for yield prediction for mustard crop in eight districts of Haryana state in India. These models are time-varying parameter models and take into account for changes that are known over time in structure of the framework. SSMs with various kinds of growth trends were tried and model performances were compared using AIC and BIC criteria but the growth trend represented by polynomial splines of order-2 with the weather as an exogenous input was chosen as the most appropriate model for mustard yield prediction in all the eight districts under study. Based on the developed models, post-sample yield predictions for the next three years, i.e. 2016-17 to 2018-19 have been obtained and the deviations from actual values are also calculated which came out to be acceptable in an agricultural setup.

Keywords: State space models; yield; mustard; weather; forecasting.

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1. INTRODUCTION

In the field of predicting agricultural yield, time series models are used to determine pre-harvest forecasts for crop yields which ultimately helps in planning in advance, formulation as well as implementation of crop related policies. Farmers are also benefitted as it can aid them in deciding their future opportunities and route well in advance using these time series models. There are numerous procedures of analysing a time series and the most frequently used is the ARIMA (Auto-regressive Integrated Moving Average) model given by Box and Jenkins in the year 1976 [1]. The drawback with ARIMA models is that they assume model parameters as constant which is often not the case when it comes to reality. For such cases, varying coefficient models appears in the picture. In the case of time-dependent parameters, a new class of time series models known as state space models (SSM) can be utilized. These models consist of a measurement or observation equation and a state or transition equation. The measurement equation relates observed variables with the unobserved state vector and the state equations details the dynamics of state variables. As for state space modelling, it is relatively new and has rarely been used for agriculture related studies.

State-space models are a very flexible class of models for time-series data. State space models are much of the time used to consider the time dependency of the underlying. The beginnings of the usage of the technique in the case of multivariate data can be witnessed in works of Akaike [2], Aoki [3], and Durbin and Koopman [4]. Hooda and Thakur [5] studied the probability distributions of normal, abnormal and drought events (in months and in years) for Solan district concerned with crop planning in the Indian state of Himachal Pradesh (HP) and noted that the coefficient of variation reduces as the months will get wet and witnesses an increase in months with sporadic rainfall.

Lardies [6] presented three methods to estimate the structure/model order of state space representation for a multivariable stationary stochastic process, from measured output data. A theoretical comparison between Box-Jenkins ARIMA models and State Space Models using Kalman Filtering and Smoothing (KFS) system was studied by Ravichandran and Prajneshu [7] and was also applied on the export data of all-India marine products. The results of the study favoured the State Space Model on the basis of goodness of fit statistics, i.e., AIC, SBC and RMSE. Hooda [8] led a probability analysis of month to month rainfall for the purpose of agricultural planning at Hisar area utilizing month to month rainfall information of forty-six years. Iqbal et al. [9] demonstrated the impact of NDVI and SOI (regional meteorological parameters) and Pacific Ocean's sea level pressure on the wheat yield for the Punjab province of Pakistan.

Rajarathinam et al. [10] analysed the trends for wheat crop in terms of area, productivity and production in India during the time period 1950 to 2014 using UC models. Mwanga et al. [11] used SARIMA models for predicting quarterly sugarcane yield in Kenya and proposed SARIMA (2,1,2) $(2,0,3)_4$ to be the best fitting model amongst the contending models for the data under study on fitting criteria. Hooda & Verma [12] dealt with unobserved components models (UCM) to consider the sugarcane yield pattern in Haryana state. Also, Hooda et al. [13] created and analyzed ARIMA and state space models (SSM) for predicting sugarcane yield data and found that state space models (SSM) outperformed ARIMA models in all the regions under study. Paudel et al. [14] applied machine learning to crop yield prediction at regional level for five crops and three countries emphasising on a modular and reusable workflow to support different crops and countries with small configuration changes. It was designed in a way to run repeatable experiments using standard input data to obtain reproducible results.

Quick and efficient crop yield forecasts prior to the harvesting aids in planning, detailing, and execution of governmental policies related to crop procurement, price-structure, circulation, and decisions related to the import and export. The forecasts obtained this way are likewise helpful to farmers for choosing their future possibilities and course of action ahead of time. Considering the significance of the topic, the work has been completed for mustard crop yield in Bhiwani, Fatehabad, Gurugram, Hisar, Jhajjar, Mahendragarh, Rewari and Sirsa districts of the state Haryana, as shown in the map in Fig. 1. The state space models (SSM) along with exogenous factors haven't been utilized by now in the field of Indian agriculture. The current examination explores the usage of weather as an exogenous input in the state-space framework for the betterment of accuracy in forecasting accomplished by simple state space models (SSM). For the purpose of parameter estimation, the Kalman Filtering and Smoothing (KFS) has been utilized as it gives optimal evaluation for the states.

2. MATERIALS AND METHODS

State space models deal with dynamic time series which involve unobserved variables or parameters that illustrate the evolution in the state of the underlying system. State space models are generally utilized in many different areas of science related to business and industry, econometrics, engineering and agriculture. Additionally, this subset of statistics is also of importance to those who are interested in financial research. The overall state space model with an exogenous input incorporates time-varying system matrices and the state equations. It tends to be figured as:

$Y_t = Z_t\alpha_t + X_t\beta + \varepsilon_t,$ $\quad\quad$ $\boldsymbol{\varepsilon_t} \sim N(0, \sigma^2)$
(Observation Equation)

$\alpha_t = T\alpha_{t-1} + W_t\gamma + \eta_t,$ $\quad\quad$ $\eta_t \sim N(0, Q)$
(State Transition Equation)

$\alpha_1 = \alpha\,,$
(Unknown Initial Condition)

Here, the general regression vector tends to be bisected into β, a time invariant part and $\boldsymbol{\alpha_t}$, which is a time varying part. $X_t\beta$ and $Z_t\alpha_t$ (contributions from regression variables) and $\boldsymbol{\varepsilon_t}$ (some value from zero-mean, independent and Gaussian noise variables sequence) together form Y_t, the response value at some time *t*. α_t (a time varying part) is the state and for t=1, the state transition equation is initialized with some unknown vector $\boldsymbol{\alpha}$ and such a condition is termed as the diffuse initial condition.

Temperature and rainfall are the important weather parameters influencing crop growth through different physiological processes. The daily weather data on maximum and minimum temperatures and rainfall of Bhiwani, Fatehabad, Gurugram, Hisar, Jhajjar, Mahendragarh, Rewari and Sirsa districts for the past 37 years (i.e., 1980-81 to 2018-10) were obtained from India Meteorological Department (IMD), New Delhi and different meteorological stations in Haryana. The fortnightly weather data computed for minimum temperature, maximum temperature and rainfall, for inclusion in SSM are as follows:

Average Maximum Temperature (TMX) $=\frac{\sum_{i=1}^{15} TMX_i}{15}$

Average Minimum Temperature (TMN) $=\frac{\sum_{i=1}^{15} TMN_j}{15}$

Accumulated Rainfall (ARF) $=\sum_{k=1}^{15} ARF_k$

Where TMX_i is the i^{th} day maximum temperature, TMN_j , the j^{th} day minimum temperature and ARF_k , the k^{th} day rainfall (i, j,k = 1, 2, 3,….,15).

2.1 Polynomial Spline Trends

Polynomial spline trend model is a general-purpose tool which is used for the purpose of extracting a trend that is smooth from a noisy data. A piece-wise function which interpolates a set of knots is known as a spline. Alternatively, it is a function which goes through a set of points. Interpolation (a type of estimation), is a method of constructing new data points in the range of a set of known data points. Interpolation is mostly required to estimate the value of that function for an intermediate value. A form of interpolation in which the interpolant is a special type of piecewise polynomial called 'spline' is known as spline interpolation. For orders up to 3, the system matrices are as shown:

Order 1 spline- Z = [1], T = [1] , and $Q = \sigma^2\,[h]$

Order 2 spline- **Z** = [1 0], **T** = $\begin{bmatrix} 1 & h \\ 0 & 1 \end{bmatrix}$, and $Q = \sigma^2 \begin{bmatrix} \frac{h^3}{3} & \frac{h^2}{2} \\ \frac{h^2}{2} & h \end{bmatrix}$

Order 3 spline- **Z** = [1 0 0], **T** = $\begin{bmatrix} 1 & h & \frac{h^2}{2} \\ 0 & 1 & h \\ 0 & 0 & 1 \end{bmatrix}$ and $Q = \sigma^2 \begin{bmatrix} \frac{h^5}{20} & \frac{h^4}{8} & \frac{h^3}{6} \\ \frac{h^4}{8} & \frac{h^3}{3} & \frac{h^2}{2} \\ \frac{h^3}{6} & \frac{h^2}{2} & h \end{bmatrix}$

Here, h=1 and it signifies difference amongst time points that are successive in nature.

In case of higher orders, the system matrices are likewise characterized by De Jong and Mazzi [15].

For the current study, PROC SSM procedure (SAS 9.4) has been utilized to build the state space models with weather input (SSM).

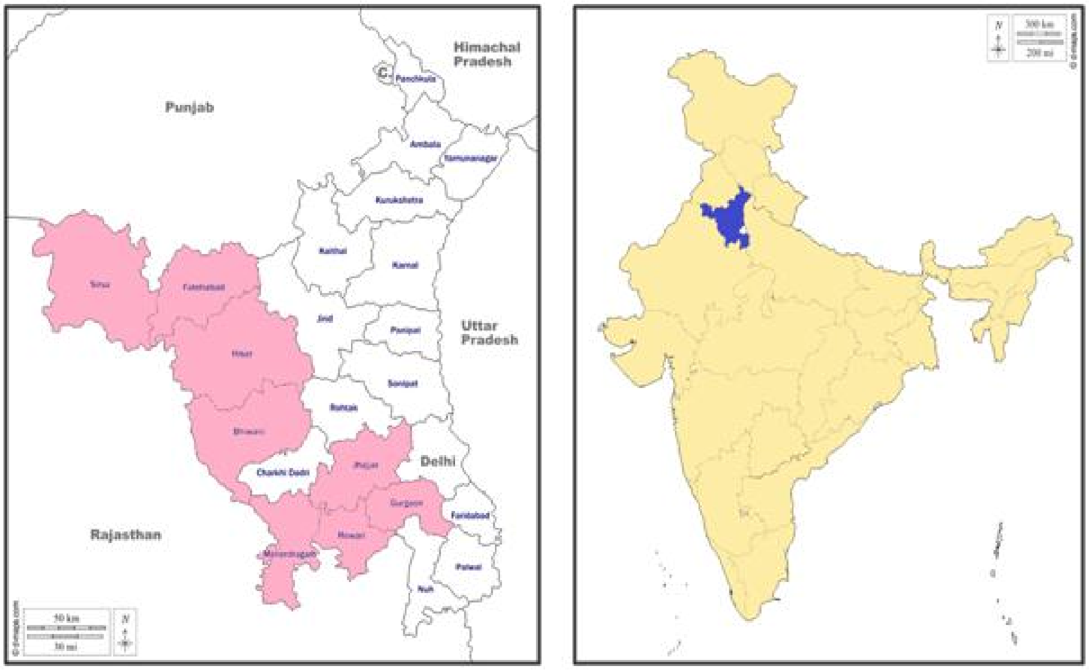

Fig. 1. Location of regions under study

2.2 Goodness of Fit and Model Selection Criteria

Akaike Information Criterion (AIC)- A measure was built for testing the goodness fit of a model by Kullback and Leibler [16] that limits the information loss. It captures the information that is lost while approximating reality. This basis, alluded to as AIC is by and large considered the principal model selection measure that ought to be utilized by and by. The AIC is

$$AIC = -2\log L(\hat{\theta}) + 2k$$

Here, vector of model parameters is given by θ; the likelihood of considered model when assessed at the maximum likelihood estimate of θ is denoted by $L(\hat{\theta})$; the count of estimated parameters in the model is denoted by k. A model with more modest AIC is viewed as the better fitting model and the best model is one with the smallest AIC value.

Bayesian Information Criterion (BIC)- The BIC proposed by Schwarz in the year 1978 [17] is additionally alluded to as the Schwarz information criterion is also based on information theory yet set within a Bayesian context. The distinction between BIC and AIC is the more noteworthy penalty imposed for the parameters by the previous than the last mentioned. BIC is figured as

$$BIC = -2\log L(\hat{\theta}) + k\log(n)$$

Here, k is the number of parameters in the model and n is the total number of observations. Lower is the value of BIC, better is the model.

Relative Deviation Criterion: - Reliability of developed models is assessed through the validation over the holdout sample. The forecasting performance of the developed model has been assessed by comparing the predicted yield and the actual yield for the holdout sample. Percent Relative Deviation (RD%) measuring deviation of the yield predictions from actual/real yield is computed as below,

$$RD\ (\%) = \left(\frac{Y_i - \hat{Y}_i}{Y_i}\right) x\ 100\ ;\ i = 1, 2, \ldots\ldots n$$

Where Y_i is the observed yield and $\hat{Y}_i$ is the predicted yield. Also, n denotes the number of prediction years.

3. RESULTS AND DISCUSSION

SSMs with weather parameters as exogenous variables were designed for mustard crop in eight districts of Haryana state namely, Bhiwani, Fatehabad, Gurugram, Hisar, Jhajjar, Mahendragarh, Rewari and Sirsa. Weather information (fortnightly) on minimum temperature, maximum temperature and rainfall for the mustard crop growth-period was used for the time period, 1980-81 to 2015-16 for building the state space models with weather as an exogenous input. Weather-yield information for 2016-17 to 2018-19 was used for the purpose of post-sample validation of the fitted models.

Mustard crop growth period (Sept.-Oct. to Feb.-Mar.) spread over 12 fortnights for the three weather variables (i.e., average minimum temperature, average maximum temperature and accumulated rainfall) turned up with 32 weather variables in total. The yield models have been fitted to relate crop yield to average maximum temperature, average minimum temperature calculated for 10 fortnights covering the period i.e. 1st fortnight of October to 2nd fortnight of February, and accumulated rainfall obtained for 12 fortnights over the period 1st fortnight of September to 2nd fortnight of February.

For Bhiwani region, three weather variables of average maximum temperature (TMX_4, TMX_6, and TMX_7), two from average minimum temperature (TMN_7 and TMN_9) and one from accumulated rainfall (ARF_{10}) were chosen using stepwise regression. For Fatehabad, two from average maximum temperature (TMX_4 and TMX_7), one from average minimum temperature (TMN_5) and four from accumulated rainfall (ARF_6, ARF_9, ARF_{10}, and ARF_{11}) were selected. In case of Gurugram, only three weather parameters namely TMX_1, TMX_2 and ARF_4 contributed significantly to the mustard yield. For Hisar, two from average maximum temperature (TMX_1 and TMX_2) and average minimum temperature (TMN_3 and TMN_5) each and one from accumulated rainfall (ARF_1) was selected. For Jhajjar district, five weather parameters were selected with two from average maximum temperature (TMX_1 and TMX_2) and three from accumulated rainfall (ARF_2, ARF_7 and ARF_8). In case of Mahendragarh district, a total of six weather variables were selected including three from average maximum temperature (TMX_1, TMX_2 and TMX_5), one from average minimum temperature (TMN_8) and two from accumulated rainfall (ARF_2 and ARF_7). Only two weather variables namely TMX_6 and ARF_2 were selected for Rewari district. In case of Sirsa district, nine weather variables were selected amongst which, two were from average maximum temperature (TMX_7 and TMX_8), three were from average minimum temperature (TMN_3, TMN_5 and TMN_6) and four were from accumulated rainfall (ARF_1, ARF_2, ARF_5 and ARF_6).

3.1 SSMs for Mustard Yield

Growth trend models with polynomial spline, PS(2) of order 2 along with chosen weather variables were tried for the eight districts under consideration. The values of the three most commonly used selection criteria, the Bayesian Information Criterion (BIC), Akaike's Information Criterion (AIC), and log-likelihood criteria for evaluating the goodness of fit of the finally developed models. (Table 1)

The parameter estimates of polynomial spline, PS(2) SSMs for the eight districts under study are given in Table 2. Also, the Maximum Likelihood Estimates (MLE) of the unknown parameters of selected SSMs for various districts have been presented in Table 3.

The post-sample mustard yield forecast is shown in Table 4. For the post-sample years 2016-17 to 2018-19 of mustard yield forecast were acquired on the basis of fitted state space models with weather input. A graphical view of the same has

Table 1. Selection fit criteria of ssms with weather input for mustard yield of various districts

Fit Criterion/District	log-likelihood	AIC	BIC
Bhiwani	-85.97	175.94	179.17
Fatehabad	-80.27	164.54	166.81
Gurugram	-79.24	162.49	165.36
Hisar	-88.9	181.80	184.54
Jhajjar	-71.79	147.58	150.17
Mahendragarh	-84.68	173.36	176.02
Rewari	-68.61	140.36	142.63
Sirsa	-88.30	180.59	183.03

Table 2. Parameter estimates of polynomial spline of order-2 ssm model

Bhiwani		
Regression variable	**Estimate**	**t-value**
TMX_6	0.28366	1.53
TMX_7	-0.17979	-1.00
TMX_4	-0.33870	-1.00
TMN_7	0.09860	0.45
TMN_9	0.02522	0.13
ARF_{10}	0.01814	0.48
Fatehabad		
Regression variable	**Estimate**	**t-value**
TMX_4	-0.20657	-0.50
TMX_7	-0.12516	-0.55
TMN_5	-0.35316	-1.35
ARF_6	-0.12427	-0.17
ARF_9	0.05804	1.26
ARF_{10}	-0.02126	-0.45
ARF_{11}	-0.02444	-0.87
Gurugram		
Regression variable	**Estimate**	**t-value**
ARF_4	-0.05456	-1.12
TMX_1	0.17584	0.93
TMX_2	0.38061	1.43
Hisar		
Regression variable	**Estimate**	**t-value**
TMX_1	0.13764	0.45
TMX_2	0.64265	1.83
TMN_3	-0.12282	-0.36
TMN_5	0.22965	0.84
ARF_1	0.01206	1.37
Jhajjar		
Regression variable	**Estimate**	**t-value**
TMX_1	0.20139	0.94
TMX_2	0.70498	2.41

ARF_8	-0.07346	-1.05
Mahendragarh		
Regression variable	**Estimate**	**t-value**
ARF_2	0.01854	2.72
ARF_7	-0.09741	-1.50
TMX_1	-0.05448	-0.23
TMX_2	0.54545	1.68
TMX_5	-0.05211	-0.20
TMN_8	0.19343	1.15
Rewari		
Regression variable	**Estimate**	**t-value**
TMX_6	0.34833	1.36
ARF_2	0.01901	1.99
Sirsa		
Regression variable	**Estimate**	**t-value**
TMX_7	0.07130	0.37
TMX_8	0.09324	0.33
TMN_3	-0.01902	-0.06
TMN_5	-0.00462	-0.02
TMN_6	-0.26642	-1.15
ARF_5	-0.07971	-0.67
ARF_6	0.04827	0.10
ARF_1	0.01002	1.31
ARF_2	0.01732	2.35

Table 3. Maximum likelihood estimates (MLE) of unknown parameters of alternative SSMs for various districts

District	Component	Type	Parameter	Estimate	Approx. S.E.
Bhiwani	Growth	PS (2) trend	Level Variance	0.018	0.024
	White Noise	Irregular	Variance	4.249	1.219
Fatehabad	Growth	PS (2) trend	Level Variance	1.054 E-8	.
	White Noise	Irregular	Variance	6.481	1.911
Gurugram	Growth	PS (2) trend	Level Variance	1.054 E-8	.
	White Noise	Irregular	Variance	3.885	0.987
Hisar	Growth	PS (2) trend	Level Variance	1.054 E-8	.
	White Noise	Irregular	Variance	6.638	1.743
Jhajjar	Growth	PS (2) trend	Level Variance	1.054 E-8	.
	White Noise	Irregular	Variance	4.361	1.187
Mahendragarh	Growth	PS (2) trend	Level Variance	1.054 E-8	.
	White Noise	Irregular	Variance	4.340	1.160
Rewari	Growth	PS (2) trend	Level Variance	1.054 E-8	.
	White Noise	Irregular	Variance	6.915	2.039
Sirsa	Growth	PS (2) trend	Level Variance	1.054 E-8	.
	White Noise	Irregular	Variance	4.554	1.288

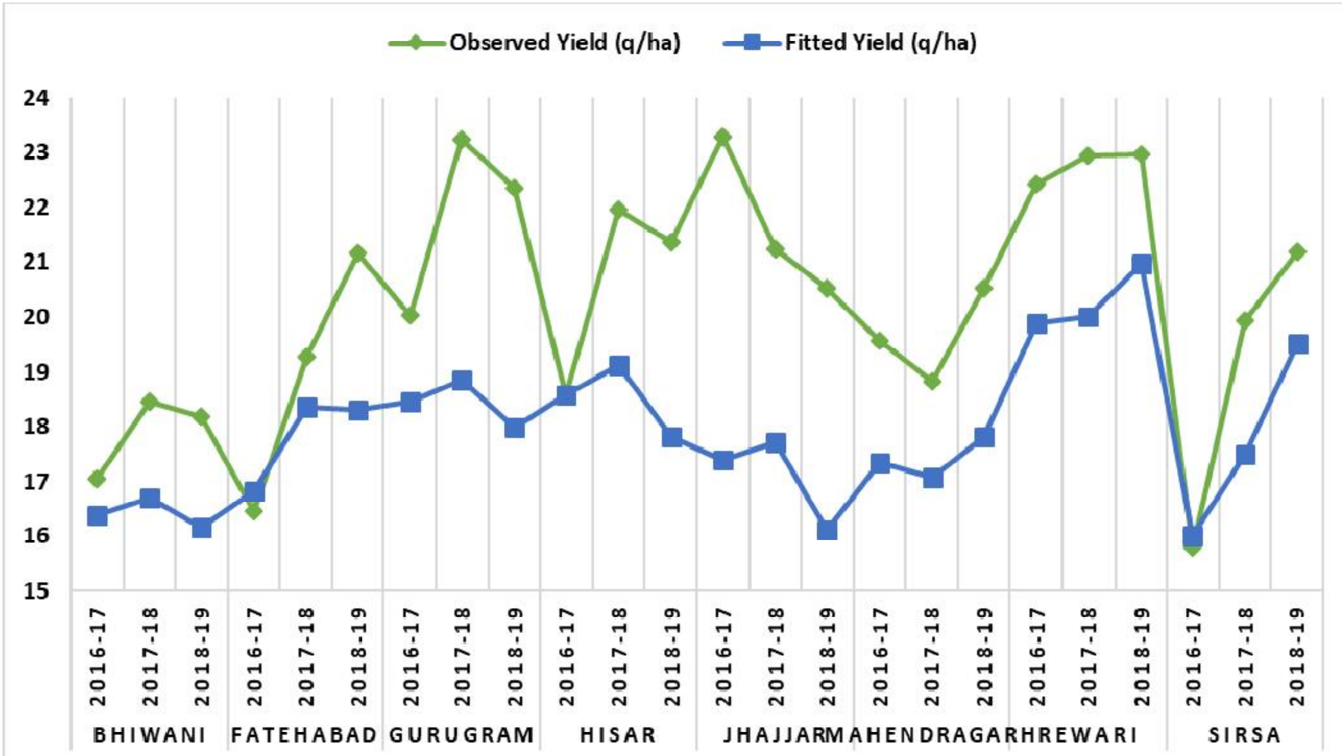

Fig. 2. Observed vs. fitted yields (q/ha) for districts under study

Table 4. Percent relative deviations of post-sample mustard yield forecasts from real-time yield(s) based on state space models

District/Model	Forecast year	Observed yield (q/ha)	Fitted yield (q/ha)	Percent relative deviation
Bhiwani	2016-17	17.05	16.40	3.83
	2017-18	18.47	16.72	9.45
	2018-19	18.20	16.16	11.20
Av. Abs. percent dev.	8.16			
Fatehabad	2016-17	16.46	16.84	-2.34
	2017-18	19.28	18.36	4.75
	2018-19	21.16	18.31	13.48
Av. Abs. percent dev.	6.85			
Gurugram	2016-17	20.03	18.47	7.80
	2017-18	23.25	18.86	18.8
	2018-19	22.36	17.99	19.54
Av. Abs. percent dev.	15.39			
Hisar	2016-17	18.58	18.59	-0.07
	2017-18	21.95	19.12	12.85
	2018-19	21.38	17.81	16.70
Av. Abs. percent dev.	9.82			
Jhajjar	2016-17	23.30	17.40	25.30
	2017-18	21.24	17.73	16.52
	2018-19	20.53	16.13	21.41
Av. Abs. percent dev.	21.07			
Mahendragarh	2016-17	19.58	17.34	11.41
	2017-18	18.83	17.08	9.30
	2018-19	20.54	17.81	13.28
Av. Abs. percent dev.	11.33			
Rewari	2016-17	22.43	19.89	11.29
	2017-18	22.95	20.00	12.82
	2018-19	22.96	20.98	8.60
Av. Abs. percent dev.	10.90			
Sirsa	2016-17	15.80	16.03	-1.47
	2017-18	19.94	17.51	12.19
	2018-19	21.20	19.53	7.88
Av. Abs. percent dev.	7.18			

been shown in Fig. 2. The predictive performance(s) of the models were analysed in terms of percent relative deviations mustard yield forecasts in relation to observed yield(s). The average absolute percent deviations from real-time yield data based on the chosen models were found to be 8.16, 6.85, 9.82, 11.33, 10.90 and 7.18 for Bhiwani, Fatehabad, Hisar, Mahendragarh, Rewari and Sirsa districts, respectively, which was very much within the acceptable range for agricultural data-based forecasting. For Gurugram and Jhajjar districts with an average absolute percent deviation of 15.39 and 23.41, respectively, the models somehow failed to capture the trend due tohuge variability in the data and there is a scope for further improvement. The results are at par with the results obtained by Hooda and Verma [18] and Rajarathiram et al. [10] used for the purpose of sugarcane and wheat crop forecasting, respectively.

4. CONCLUSION

A close scrutiny of results shows that state space models with weather input performed really well with very low error metrics in most (6/8) districts. Further, it is likewise referenced that weather data during the crop growing season can be handily acquired for the pre-harvest forecasts to be released as expected. Also, the fitted models are equipped of giving reliable mustard yield estimates well ahead of time of the mustard harvest while then again, the state Department of Agriculture and Farmer's Welfare yield estimates are received often quite late after the actual harvest of the crop.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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